Does Risk Aversion Vary During the Year? Evidence from Bid-Ask Spreads

Abstract

We document previously undiscovered seasonal patterns in bid-ask spreads which are economically and statistically significant. After controlling for well-known conditional effects on spreads, such as risk, liquidity, and asymmetric information effects, we find that individual dealer quotes are on average 20 basis points wider during the fall and winter relative to their unconditional average of 180 basis points. Furthermore, inside spreads are about 20 basis points narrower during these periods when individual quotes are wider. We posit that these opposing patterns in quoted spreads and inside spreads are the logical outcome of seasonally changing risk aversion among a subset of market makers. When we consider periods of high market volatility, we find that the economic and statistical significance of the seasonal patterns in spreads intensify, as they should if they arise for reasons related to risk aversion. Our findings are robust to a wide range of tests and specification changes. Independent of the cause, researchers studying spreads need to be mindful of the strong seasonal patterns in individual dealer spreads and inside spreads, as does any market participant who has discretion in the timing of his trades.

Does Risk Aversion Vary During the Year? Evidence from Bid-Ask Spreads

Bid-ask spreads constitute one of the largest costs of transacting on modern equity markets. The equal-weighted average of the spread between the best bid and offer on Nasdaq National Market stocks is almost 5% of the price of the equity being bought or sold. In smaller Nasdaq firms, the spread is often as large as ten percent of the market price of a stock. Even in larger-cap Nasdaq firms, the spread is typically as large as a percent of a stock's price. Past research suggests spreads vary across the seasons, including work by Fortin, Grube, and Joy (1989) and Clark, McConnell, and Singh (1992) who find that average spreads are wider in the second half of the year than they are at the start of the year, and Hong and Yu (2007) who find average spreads are wider during summer, perhaps due to increased adverse selection during a period when so many people take their annual vacations. Theory dating back to Stoll (1978a) and Ho and Stoll (1981, 1983) suggests the magnitude of spreads is determined in part by the risk aversion of dealers in securities markets. To date, there have been no studies that investigate whether seasonal variations in spreads may arise due to seasonal changes in risk aversion.

Certainly there are components of spreads other than those that arise due to risk aversion which may vary seasonally. Various models, including that of Stoll (1978a), indicate that the spread should vary with liquidity, order processing costs, and asymmetric information effects. Associated with these models, there are strong empirical relationships that have been shown to relate spreads to volume, volatility, turnover, and a host of other factors. See Stoll (1978b), for instance. We take account of these previously documented regularities in our analysis, and we find large, systematic seasonal patterns in spreads which are independent of those previously documented.

While it is well understood that higher risk aversion among dealers should lead to wider dealer quotes, we present a theory that predicts that the difference between the best bid and the best ask (*i.e.* the inside spread) should narrow during periods when risk averse dealers are quoting wider spreads. This theory builds on prior work by Kamstra, Kramer, and Levi (2003) who cite an extensive literature which indicates that roughly ten percent of the population suffers from seasonal depression during the fall and winter, and that depression in turn leads to higher risk aversion. (Kamstra, Kramer, and Levi, 2003 and 2007, present empirical evidence that equity returns and Treasury bond returns exhibit striking seasonal patterns which appear to be consistent with market participants experiencing changes in risk aversion associated with seasonal depression.) If dealers are heterogeneous in their propensity to suffer from seasonal depression and hence in the degree to which they exhibit seasonally varying risk aversion, then only those who suffer from the condition might systematically widen their quotes in the fall and winter.

We argue that a seasonally risk averse dealer who holds a long inventory not only widens his quotes in the fall and winter, but he also tends to lower his bid and ask prices during such periods. He quotes a lower bid price to reflect his greater distaste for risk and hence a preference to purchase additional inventory only if it is available at a relatively lower price. His lower ask price indicates his relatively greater interest in liquidating (at least a portion of) his risky positions than he exhibited before his change in risk aversion. Of course, in practice dealers can hold either short or long inventories. A seasonally risk averse market maker holding a *short* inventory would also widen his quotes during the fall and winter, following Stoll (1978a) and Ho and Stoll (1981, 1983). In contrast to the long-inventory market maker, however, his bid and ask prices would tend to rise rather than drop. As we explain more fully in the rest of the paper, in a context where multiple heterogeneous market makers are interacting, the end result of these various quoted spreads (including some quotes that are wider in the fall and winter due to seasonal depression and some quotes that are unchanged) is that inside spreads are narrower during the very periods when quotes are wider. Our findings are invariant to whether market makers' inventories are on balance long, short, or a mixture of long and short.

In testing whether time-varying risk aversion leads to seasonal changes in spreads, we employ two datasets. First, we study spreads implied by the quotes of individual NYSE specialists (quoted spreads), and second we examine spreads between the best bid and best ask prices of Nasdaq market makers (inside spreads).[1] During the fall and winter periods

[1]As we report in a set of robustness checks described in greater detail below, Nasdaq quoted spreads

when a subset of the population experiences seasonal depression and hence greater risk aversion, we find dealer quoted spreads are wider. Furthermore, we find inside spreads are narrower during those same periods. Additionally, the statistical and economic significance of the seasonal cycles become stronger during periods of high market volatility. That is, the link between risk aversion and spreads intensifies during periods of heightened risk. We posit that all of this evidence is consistent with the possibility that dealer spreads vary seasonally with risk aversion.

The remainder of the paper proceeds as follows. In Section I we introduce the data used for this study. In Section II, we discuss the unconditional seasonality exhibited by various market variables, including individual dealer quoted spreads, volume, volatility, and turnover. We also define the measure we use to capture the conditional seasonal effect we seek to estimate, and we show that dealer quoted spreads are indeed wider during the periods when a portion of the population suffers from seasonal depression. In Section III we examine the way in which the seasonal effect in quoted spreads becomes stronger during periods of high market volatility, and we explain how this is consistent with the theory that market participants exhibit time-varying risk aversion. In Section IV we consider inside spreads, defined by the best bid and best ask. We show that the seasonal pattern in inside spreads is opposite to that in quoted spreads, with narrower inside spreads occurring during the seasons when quotes are wider. Section V contains a discussion of some common concerns and questions related to SAD, including whether financial professionals such as market makers are less likely to suffer from seasonal depression than the general population. Section VI summarizes the range of robustness checks we conducted, and Section VII concludes.

I Bid-Ask Spreads Data

To determine whether an anomalous seasonal pattern exists in bid-ask spreads, we consider both quoted bid-ask spreads (*i.e.*, individual dealer quotes) and inside spreads implied by the best bid and best ask quoted across all dealers. Each NYSE firm is covered by a single

exhibit the same seasonal pattern we document in NYSE quoted spreads. That is, the seasonal differences we find between quoted spreads and inside spreads do not appear to be due to differences between the NYSE and Nasdaq market structures.

specialist, and that specialist provides at all times a bid and ask price at which he is willing to trade some quantity of stock. Note that there may be market participants willing to trade at a higher bid or lower ask than posted by the specialist, but since we are interested, in part, in the time-series behavior of an *individual's* quoted spread, we consider the quoted spread of the specialist. Note that the specialist's quoted spread is *not* an inside spread, and we do not consider NYSE inside spreads. We do, however, consider Nasdaq inside spreads. More than one market maker typically covers each Nasdaq firm. In the extreme, individual firms have been covered by as many as 120 market makers, though in practice some of the registered market makers covering a given issue may not be active at a given point in time. The best bid and best ask prices across all market makers' quotes define an inside spread.

We consider end-of-day quoted spreads from NYSE and end-of-day inside spreads from Nasdaq, with all data obtained from CRSP.[2] We exclude financial services firms (SIC codes 6011-6799) from our analysis, as is the convention. While *intraday* bid and ask prices are available for both of these markets, we restrict our study to end-of-day bid-ask spreads. The statistical properties of several of the variables we seek to study (spreads, turnover, volume, *etc.*), follow distinct intraday patterns, which may complicate the analysis of intraday data. By choosing a fixed point in the trading day, we bypass those complications.[3] The main daily NYSE and Nasdaq data series we employ begin on January 4, 1993 (which is the first date on which NYSE bid and ask closing prices are reliably available through CRSP) and end on December 29, 2006.

[2]One might question whether our use of closing bid-ask spreads is complicated by the closing auction which takes place on the NYSE or the closing cross which takes place on Nasdaq. While some NYSE market participants submit limit-on-close or market-on-close orders to participate in the NYSE closing auction, continuous trading remains active during this period. Similarly, for Nasdaq the closing cross occurs in parallel with continuous trading, with active continuous trading taking place even while the closing cross is in progress. For both NYSE and Nasdaq stocks, the closing bid and ask prices provided by CRSP come from the continuous trading session and are not based on quotes that arises from the NYSE closing auction or the Nasdaq closing cross. We thank Ingrid Werner for clarifying these issues.

[3]Robustness checks based on intraday Nasdaq data from the Nastraq database suggests that seasonal patterns in end-of-day quotes are qualitatively similar, though less significant, at other points of the trading day, for instance at market open, at mid-day, an hour after open, and an hour before close. The slightly reduced significance may arise from the shorter sample period. (Nastraq data is available starting only in 1999.)

II Seasonal Patterns in Quoted Spreads

Our study begins with a comprehensive analysis of the NYSE quoted bid-ask spreads. We consider Nasdaq inside spreads in Section IV. The percentage quoted spread (QSpread) for a particular NYSE stock, k, on a particular trading day, t, is calculated as:

$$QSpread_{k,t} = \frac{(Pask_{k,t} - Pbid_{k,t})}{(Pask_{k,t} + Pbid_{k,t})/2} \tag{1}$$

where $Pask_{k,t}$ and $Pbid_{k,t}$ are the closing bid and ask prices posted by the specialist. In order to ensure that we work with valid quotes, we exclude cases where the bid price or ask price is zero.[4]

A Unconditional Analysis

Figure 1 provides an initial snapshot of the unconditional seasonal behavior of quoted bid-ask spreads. (Later, we present careful conditional analysis in a regression framework; for now we consider some broad seasonal characteristics of the quotes data.) Each of the four panels of Figure 1 presents monthly average quoted spreads, by decile. Deciles are formed on the basis of stocks' lagged average monthly market capitalization. Panel A contains monthly average quoted spreads for equal-weighted deciles, including all NYSE stocks. Percentage spreads are indicated on the vertical axis, and months are represented on the horizontal axis

[4] In cases where the closing bid and ask prices are not representative, in the sense that they do not appear to be typical of the day's trading activity, CRSP assumes that the quote was posted by a dealer who was required to post a quote but was not interested in trading. (As described by Harris, 2001, page 511, a Nasdaq market maker who stops making a market in a given stock is required to wait 20 days before he resumes trading. Thus a market maker who needs to step away from the market temporarily tends to post an exceptionally wide spread.) CRSP sets the closing bid and closing ask to zero in such cases, pending further review. Details about this practice are provided in an Update Supplement released by CRSP in October 2005, available on CRSP's web site. Conversations with CRSP representatives revealed that they set to zero roughly 5% of all bid and ask data points in the initial release, with over one-third of these cases occuring between October 2000 and May 2001. Our analysis found that these zero bid and ask prices (which we then set to missing) were most concentrated in 72 trading days, February 6 through May 18 2001 inclusive. The scarcity of non-missing values with which to form average decile spreads during this period led to some instability in our regressions, with unexpected coefficient estimates on variance, turnover, and volume. Hence the quoted spread regression results we report below are based on excluding those 72 trading days from our analysis. (We do keep the volume, turnover, volatility, *etc.* for those dates if they are needed (lagged) for dates outside that 72 trading-day window.) Our findings with respect to the our key explanatory variable of interest, $Incidence_t$ (to be defined below), are qualitatively identical if we instead include those dates with sparsely available closing bid and ask quotes. Note that this CRSP problem is isolated to NYSE quotes only and does not affect the Nasdaq results we report below.

by their first letter, starting with January. The lowest dotted line represents Decile 10 (the largest stocks), the next highest dotted line represents Decile 9, and so on up to the highest dotted line which represents the smallest market-cap stocks, Decile 1. The solid dark line around the middle of the plot, hovering near two percent, represents the average monthly quoted spreads across the deciles. There are several noteworthy features of the Panel A plot. First, there is a monotonic pattern across deciles: the line representing the tenth decile lies everywhere below the line representing the ninth decile, and so on all the way through to the first decile. Second, all of the deciles generally demonstrate a similar seasonal pattern such that they are at their annual lowest in the summer, and they tend to remain below average through to the end of the year.[5,6] Finally, the decile of the largest stocks exhibits much less seasonal variability than the decile of the smallest stocks. For Decile 1, there is about a 100 basis point difference in the highest and lowest average monthly spreads, while for Decile 10 the difference is much smaller, around 20 basis points.

Consider now Panel B, which reports monthly average quoted spreads for the NYSE deciles, *excluding stocks with a closing price less than $5 on a given day*. Note that the scale on the vertical axis is finer in Panel B than in Panel A. Similar to the Panel A case of all stocks, the deciles of stocks with prices greater than or equal to $5 exhibit monotonic patterns such that the tenth decile line is everywhere below the ninth decile, *etc*. The spreads are at their annual lowest around June and peak in the early spring. Most of the deciles in Panel B demonstrate roughly similar differences between the annual high and low points of their seasonal cycles, around 20 basis points, though for some of the small deciles, the difference is as large as 40 basis points.

Panels C and D present monthly average quoted spreads for NYSE value-weighted deciles. Panel C reports for all stocks, and Panel D for all stocks except those with a daily market cap less than $5. The scale of the vertical axis in Panel C is the same as in Panel A, and the scale of the vertical axis in Panel D is the same as in Panel B. The value-weighted deciles

[5]Unreported t-tests conducted on the monthly average spreads support this observation.

[6]The appearance of lower spreads during the summer may seem at odds with Hong and Yu's (2007) finding that spreads are widest in summer. Note that Hong and Yu consider inside spreads (obtained from Datastream), whereas Figure 1 plots quoted spreads. Furthermore, while Hong and Yu do indeed find that the unconditional average of the inside bid-ask spread across 30 international markets is statistically positive in summer, for the specific case of the US they find spreads are negative in summer, albeit insignificant.

have seasonal characteristics roughly analogous to their equal-weighted counterparts.

B Measuring Seasonality

Kamstra, Kramer, and Levi (2003, 2007) find seasonal cycles in equity returns and Treasury bond returns which they hypothesize are associated with seasonally varying risk aversion among investors. Researchers in medicine and psychology have established that roughly ten percent of the population suffers from seasonal depression (known as seasonal affective disorder, or SAD), and that depression is associated with higher risk aversion, including risk of a financial nature. Onset of SAD is in the fall, recovery is in the spring, and incidence is directly related to hours of daylight, increasing as days shorten. (For further details on SAD and its relation with risk aversion, see Kamstra, Kramer, and Levi, 2003, 2007.) Building on the conjecture that some market participants experience seasonally varying risk aversion, we explore whether this phenomenon might help explain the seasonal behavior of bid-ask spreads demonstrated in Figure 1.

To model the seasonal pattern in (some) market makers' risk aversion, we follow Kamstra, Kramer, and Levi (2007) and adopt a measure of seasonality which is based directly on the clinical incidence of SAD. Young *et al.* (1997) and Lam (1998) studied hundreds of North Americans who suffer from SAD, documenting the precise point in the late summer or fall when each individual's SAD symptoms first arose as well as the point in winter or spring when symptoms resolved. We use those datasets to create a proxy for the timing of seasonal changes in risk aversion among those who are affected. First, we take the proportion of SAD-suffers in the Young *et al.* and Lam samples who are actively experiencing SAD symptoms in a given month. Next, we calculate the cumulative proportion of subjects who experienced the onset of their SAD symptoms (cumulated starting in late summer, the earliest point at which any subjects are first diagnosed with onset) and then deduct the cumulative proportion of subjects who experienced full recovery from SAD. We then produce a daily measure of SAD incidence by smoothly interpolating the monthly incidence of SAD to daily frequency using a spline function. The result is a daily measure of SAD incidence, taking on values between zero percent in summer and close to 100 percent in winter (indicating that close to

100 percent of the people who suffer from SAD have succumbed by winter). Because this proxy measures the true incidence of SAD with error, we use an instrumented version of the measure to avoid an errors-in-variables bias.[7] Results are very similar if we use the SAD incidence proxy directly, without instrumenting.

C Forming Deciles

To consider seasonalities in spreads across firms with different characteristics, we form deciles. The deciles are equal-weighted, using the previous month's average market capitalization as the weighting variable. In robustness checks we also consider value-weighted deciles formed using the previous month's average number of market makers and find similar results.

When we form deciles, we end up with daily series of equal-weighted averages of the firm-specific daily median quoted spreads. That is, we end up with ten daily series of average quoted spreads, which we denote $QSpread_{i,t}$ for $i = 1, \cdots, 10$ deciles. Many market microstructure studies exclude firms for which the previous day's closing price was less than \$5. While we include such firms in our analysis, we confirm in robustness checks that our findings are unchanged when those firms are excluded.

D Other Variables

Naturally, in studying potential seasonality in these spreads series, we control for the empirical regularities shown by others to be important determinants of spreads. Most previous studies of spreads consider inside spreads, not the quotes of individual market makers. We will see that most variables known to influence inside spreads have the same effect on quoted spreads. Following Stoll (1978a, 1978b), Ho and Stoll (1981, 1983), and others, we control for adverse selection (using turnover), holding period (using volume), and risk (using return

[7] To produce the instrumented version of SAD incidence, first we run a logistic regression of the daily incidence on our chosen instrument, the length of day. (The nonlinear model is $1/(1+e^{\alpha+\beta day_t})$, where day_t is the length of day t in hours in New York and t ranges from 1 to 365. This particular functional form is used to ensure that the fitted values lie on the range zero to 100 percent. The $\hat{\beta}$ coefficient estimate is 1.24 with a standard error of 0.0255, and the regression R^2 is 95.7 percent.) The fitted value from this regression is the instrumented measure of incidence. Employing additional instruments, such as change in the length of the day, makes no substantial difference to the fit of the regression or the subsequent results using this fitted value. For the purpose of illustrating the annual seasonal cycle in the incidence variable, here are the *mean monthly values* of the daily instrumented incidence variable we use in our regressions (starting with January): 0.968, 0.920, 0.708, 0.302, 0.078, 0.023, 0.019, 0.052, 0.219, 0.600, 0.884, 0.963. Of course, we use the daily values rather than the monthly means in our regressions.

variance). Later, when we consider Nasdaq data, we can also control for competition (using number of market makers). Given the findings of Fortin, Grube, and Joy (1989), Clark, McConnell, and Singh (1992), and Hong and Yu (2007) on spread seasonalities, we also include a dummy variable for January and dummy variables for the third and fourth quarters.[8]

Before presenting detailed regression results, we must explain where we obtain and how we calculate some of the variables the prior literature suggests we should control for, including volume, variance, and turnover. We obtain from the CRSP Daily Stock database daily observations for the variables for each stock: trading volume, shares outstanding, and closing price. Based on this set of information, we are able to calculate turnover and variance for each stock. We perform our regression analysis on deciles instead of individual stocks for several reasons. First, the idiosyncratic noise in bid-ask spreads is high for individual stocks, and second, the correlation between volume and turnover is high for individual stocks since shares outstanding changes rarely for many firms. Finally, it is infeasible to do a systems estimation that exploits cross-firm correlation between spreads for thousands of stocks in the cross section (which is a familiar problem in the asset pricing literature).

The lagged natural logarithm of dollar volume is computed for each decile as follows: We take each stock's closing price for the previous day times its share volume for the previous day (in millions), calculate the average across all stocks in the decile, then take the natural logarithm of that figure.[9] Lagged variance is calculated for each decile on each trading day as follows. First we determine which stocks are in the decile on a given day, then for that group of stocks, we calculate the previous month's average daily variance using squared returns. This yields a daily raw variance series. Next, we detrend the decile's raw variance series by dividing by the decile's raw variance averaged over the past 252 trading days. Finally, we multiply by 100. The result is our (detrended) lagged variance series, in percentage terms.[10]

[8]Our principle findings are largely invariant if we include a single dummy variable for the second half of the year instead of individual third and fourth quarter dummies, if we include an additional dummy for the second quarter, if we include a monthly dummy for January and/or December instead of including a dummy for the second half of the year, or if we exclude these dummies altogether.

[9]In robustness checks where we use value-weighted deciles instead of equal-weighted, the averages taken for forming deciles are market-cap weighted.

[10]This method of specifying variance takes account of the fact that volatility models (and risk) are highly persistent. Our findings with respect to the seasonal patterns of bid-ask spreads, presented below, are virtually identical if we use an alternate measure of risk, such as GARCH volatility or realized volatility.

Lagged turnover is calculated for each decile by taking a given stock's share volume for the previous day divided by its number of shares outstanding for the previous day, averaging across all stocks in the decile, and multiplying by 100.

E Quoted Spread Summary Statistics

Table 1 contains summary statistics for the daily firm-level data pooled across all firms and over all trading days from 1993 to 2006. Panel A corresponds to the NYSE data; we discuss the Nasdaq data in Panel B later. There are over five and a half million observations in the raw pooled dataset.[11] The average quoted spread is about 1.8 percent, with a minimum of less than a hundredth of a percent and a maximum of almost 200 percent. The bid price and ask price both have an average around $28, with the ask obviously slightly larger than the bid. The mean daily percentage return is 0.062 percent, with a minimum around -95 percent and a maximum over 300 percent. The mean number of shares outstanding is well over 100 million shares. The mean dollar volume is over $19 million, and the maximum dollar volume is almost $10 billion.[12] Average daily return variance is less than a tenth of a percent, ranging from a low below 0.01 percent to a high over 800 percent. Average daily turnover is about half a percent. Virtually all of these series are highly skewed and kurtotic.

We use the raw firm-level data to form equal-weighted deciles, based on the previous month's average market capitalization. Table 2 contains summary statistics for the decile data. For now we focus on Panel A, which contains summary statistics that correspond to the NYSE data. We discuss the Nasdaq data in Panel B later. For each decile, we present summary statistics on quoted spreads, the natural logarithm of volume, raw volume,

[11] We require that all firms in our sample have data available for bid and ask, which we use to compute the quoted spread. Thus the maximum number of observations in our sample are observed for the bid, ask, and quote. In the case of other variables, our estimation is not adversely affected by occasional missing observations. For example, if a particular firm's turnover figure is missing on a particular day, we are still able to form its decile's average turnover based on averaging the turnover values for the other firms in that decile. Robustness checks confirm that omitting observations for which there are any missing data leaves our findings unchanged.

[12] In Tables 1 and 2 we present summary statistics on dollar volume as well as the natural logarithm of dollar volume, ln(volume). In cases where volume is less than one (recall that units on volume are in millions of dollars), ln(volume) will necessarily be less than zero. That is, we occasionally observe negative values for ln(volume) even though volume itself is always positive. Regression results we present later are, of course, invariant to the units we use to express volume. That is, if we were to rescale volume to be in dollars instead of millions of dollars, we would avoid observing negative values for ln(volume), but the estimation results would be identical.

turnover, and return variance (detrended, calculated as described above). As expected, Decile 1 (the decile of the smallest firms) contains firms with the widest average quoted spreads. The average spreads narrow monotonically through the deciles. Decile 1 also contains firms with the lowest volume, which then rises monotonically through the deciles. The average detrended variance values for each decile are close to 1 by construction. Average *raw* variance (not reported) is unsurprisingly highest for Decile 1 and declines monotonically through to Decile 10.

F Regression Analysis

We use GMM to jointly estimate a set of regressions for the quoted spread deciles (10 equations in all):

$$
\begin{aligned}
QSpread_{i,t} = \alpha_i &+ \mu_{Incidence_i} Incidence_t + \mu_{Volume_i} Volume_{i,t-1} \\
&+ \mu_{Turnover_i} Turnover_{i,t-1} + \mu_{\sigma_i^2} \sigma^2_{i,t-1} \\
&+ \mu_{Jan} D^{Jan}_{i,t} + \mu_{Q3} D^{Q3}_{i,t} + \mu_{Q4} D^{Q4}_{i,t} + \epsilon_{it}. \qquad (2)
\end{aligned}
$$

The dependent variable in each equation is the average daily percentage quoted spread, defined in Equation (1) above. The subscript i denotes deciles 1 through 10, leading to a total of 10 equations to jointly estimate. $Incidence_t$ is the instrumented daily measure of SAD incidence, $Volume_{i,t-1}$ is each decile's average log dollar volume at $t-1$, $Turnover_{i,t-1}$ is each decile's average turnover at $t-1$, $\sigma^2_{i,t-1}$ is each decile's average (detrended) return variance at $t-1$, D^{Jan}_t is a dummy for dates in the month of January, D^{Q3}_t is a dummy variable for dates in the third quarter (July through September), and D^{Q4}_t is a dummy variable for dates in the fourth quarter (October through December), with the intercept accounting for the average change in spreads in the first half of the year excluding January. We control for autocorrelation in the dependent variable through our use of heteroskedasticity and autocorrelation consistent (HAC) robust t-tests based on Newey West (1987) standard errors, though our findings are unchanged if instead we include as regressors sufficient lags of the dependent variable to produce white noise residuals.

We now consider results from estimating this model. The top section of Table 3 contains parameter estimates and standard errors. In all tables, one, two, and three asterisks denote significance at the ten, five, and one percent level of significance respectively. The "Diagnostic Statistics" portion of Table 3 contains R^2, a χ^2 test for the presence of up to 10 lags of autocorrelation, a χ^2 test for the presence of up to 10 lags of ARCH, and an economic magnitude statistic to be discussed below. Additionally, the bottom panel of Table 3 contains a joint test across all ten equations. There remains significant evidence of autocorrelation and ARCH in all cases, reinforcing our choice of HAC standard errors.

Consider the coefficient estimates and t-statistics in the top portion of Table 3. Consistent with the theory of Stoll (1978) and Ho and Stoll (1981, 1983) that higher dealer risk aversion should lead to wider spreads quoted by dealers, we find that the SAD incidence variable is positive and significant for all ten quoted spread deciles. That is, quoted spreads are wider during periods when seasonal depression is at its worst. The magnitude of the incidence-variable coefficients declines almost monotonically from the smallest decile to the largest decile. The positive coefficients suggest that, on average, market makers quote wider spreads during periods when more individuals are suffering from SAD. While the effect is not necessarily causative, the correlation is undeniably strong. As theory predicts, variance is almost everywhere positive, volume is almost everywhere negative, and turnover is almost everywhere positive, in each case strongly significantly so. (In Decile 10, the signs on volume and turnover jointly flip, likely due to the high degree of collinearity between these two variables.) The third and fourth quarter dummy variables are mostly significantly negative. The January dummy variable is negative in some cases, though it is positive in others. Unreported regressions available on request confirm that our findings with respect to the incidence variable are robust to whether or not we include the quarterly dummy variables and/or the January dummy variable.

The last column of Table 3 contains several joint test statistics, testing whether a given set of coefficients is jointly zero across all ten equations. (We do not conduct joint tests on the regression constant term.) All of the tests strongly reject the null hypothesis at conventional levels of significance. The bottom panel of the table presents a test for whether the coefficient estimates on $Incidence_t$ are jointly equal to each other (that is, equal but not necessarily zero). We strongly reject that null hypothesis at all conventional significance levels.

G Economic Significance

We now consider the economic impact of this seasonal effect on bid-ask spreads. To estimate the economic impact, we take the coefficient estimate on the incidence variable for a given decile and multiply it by the December value of the incidence variable. This yields the *peak* impact of the incidence variable on spreads. (The highest daily value of $Incidence_t$ is in December, very near 100%, due to the fact that among people prone to SAD almost all have succumbed to the condition by the end of December. Of course the economic impact of the incidence variable is lower in other months, and is in fact zero in June). The result of this calculation is provided at the bottom of the "Diagnostic Statistics" portion of Table 3. The economic impact is largest for the smallest decile, with spreads being about *70 basis points wider* in December than they would be in a month with zero incidence. The peak economic impact declines monotonically through the deciles, reaching a low of about 10 basis points for decile 10. The average across the ten deciles is roughly 20 basis points. This is an economically large effect given the unconditional average quoted spread is about 180 basis points.

In the next two sections we present additional analysis which is designed to test more stringently the hypothesis that the seasonal patterns in quoted bid-ask spreads are related to time-varying risk aversion among market participants.

III Time-Varying Risk Aversion

If the seasonal behavior of quoted bid-ask spreads is related to seasonalities in risk aversion, then the importance of the incidence variable should vary with the degree of market volatility, becoming more extreme when markets are volatile since volatile periods are inherently riskier. Thus, we need to test whether quoted spreads are wider during periods of high conditional market volatility, perhaps as a result of market makers being more risk averse. To do so, we interact the SAD incidence variable with the lagged volatility variable for a given decile, yielding the series $Incidence_t \cdot \sigma_{i,t-1}$ for each decile i.[13] In Figure 2 we plot the value of this variable for Decile 2 from January 1993 through December 2006.[14] Labeled tick marks indicate the start of a given year; for instance '01' indicates January 2001. To allow the economic significance of the interacted incidence variable to be comparable with the non-interacted incidence variable from other estimations, we normalize each decile's volatility-interacted incidence variable so that it has the same mean value as the non-interacted incidence variable for that decile. Although the SAD-interacted incidence measure shows a clear and distinct annual cycle (the minimum each year always occurs in June/July, when the incidence variable equals zero), the amplitude of the cycle varies strongly with return volatility. The amplitude and volatility of the $Incidence_t \cdot \sigma_{i,t-1}$ cycle are much greater in some years than others as a direct consequency of differences in volatility across periods (for instance the 2000/2001 cycle has the highest peak and varies greatly across months, whereas the 2004/2005 cycle is relatively calm across months).

We use GMM to jointly estimate a set of regressions for the quoted spread deciles (10 equations in all), replacing the $Incidence_t$ variable from Equation (1) with the volatility-interacted incidence variable, $Incidence_t \cdot \sigma_{t-1}$:

$$\begin{aligned} QSpread_{i,t} = {} & \alpha_i + \mu_{Incidence \cdot \sigma_i} Incidence_t \cdot \sigma_{i,t-1} + \mu_{Volume_i} Volume_{i,t-1} \\ & + \mu_{Turnover_i} Turnover_{i,t-1} + \mu_{\sigma_i^2} \sigma_{i,t-1}^2 \\ & + \mu_{Jan} D_{i,t}^{Jan} + \mu_{Q3} D_{i,t}^{Q3} + \mu_{Q4} D_{i,t}^{Q4} + \epsilon_{it}. \end{aligned} \quad (3)$$

Results from estimating this set of equations appear in Table 4.

The coefficient estimate on the volatility-interacted incidence variable is positive and significant across all the deciles. Its magnitude is similar to that of the non-interacted incidence coefficients presented in Table 3, and the coefficients roughly decline through the deciles. The strong joint significance of the volatility-interacted incidence estimates is captured by the

[13] By interacting with σ instead of σ^2, we lessen the likelihood of severe multicollinearity with the variance variable that is already included as a regressor. The economic impact of the SAD incidence effect is unchanged in unreported regressions where we simultaneously include variance, incidence, and volatility-interacted incidence in a single model, though the severe multicollinearity between these variables lowers the precision of estimates.

[14] Decile 2 is fairly representative, with Deciles 3 through 10 all exhibiting a bit less volatility than the plotted series and Decile 1 exhibiting a bit more.

χ^2 variable in the last column of the table. Its value is larger than the comparable value in Table 3, and most of the t-tests on individual volatility-interacted incidence coefficient estimates are larger than their Table 3 non-interacted counterparts. The relative strength of the significance of the incidence variable across Tables 3 and 4 is consistent with the notion that we obtain sharper estimates of the influence of the incidence variable on spreads if we allow the effects of the incidence variable to strengthen during periods of high volatility. Overall, the findings are consistent with SAD having an influence on risk aversion. The economic impact of the volatility-interacted incidence variable in the month of December ranges from a high near 95 basis points in Decile 1 to a low around 10 basis points for the large deciles. The economic impact averaged across all ten deciles is 24 basis points, which is slightly larger than but statistically indistinguishable from the average economic effect reported for Table 3 (20 basis points) where the incidence variable was not interacted with volatility.

The behavior of other variables in the model is similar across Tables 3 and 4. Volume is almost everywhere significantly negative, variance is almost everywhere positive and significant, and the coefficient on turnover is almost everywhere significantly positive. Once again, volume and turnover jointly flip signs in one case, likely due to their high collinearity. The January dummy variable suggests spreads are narrower in January for some but not all deciles. The third and fourth quarter dummy variables are mostly negative.

In short, if we interact the incidence variable with volatility we obtain virtually identical coefficient estimates compared to the case where we use the incidence variable itself. That is, we find the volatility interacted-incidence variable is a statistically and economically significant determinant of individual dealers' spreads. Further, the joint significance of the interacted-incidence coefficients is greater, consistent with the use of the volatility-interacted incidence variable leading to more precisely estimated coefficients.

IV Seasonal Patterns in Inside Spreads

A Hypothesis

Theory suggests quotes should be wider during periods when market makers are more risk averse, and the empirical evidence presented above supports that theory. In addition to widening his quote, however, a market maker suffering from SAD might also change his bid and ask prices. Consider first a SAD-affected market maker who holds a long inventory. This market maker might choose to reduce his bid price because with his now-higher degree of risk aversion, he is willing to buy the risky asset only at a relatively lower price, to offset his now greater distaste for risk. He might also choose to reduce his ask price in order to more quickly liquidate (at least some of) his risky positions, consistent with his preference to face less exposure to risk. The widening of his spread (which allows him greater compensation for any risk he does continue to face, consistent with theory) would be facilitated only if his bid were to fall more than his ask. See Table 13-2 on page 285 of Harris (2003) for a summary of the tactics dealers use to manage their inventories, including changing bid and ask prices to influence clients' buy or sell decisions.

Consider now a SAD-affected market maker who holds a short inventory. Theory dictates that a short market maker would also widen his spread when he becomes more risk averse. In contrast to the long market maker, the short market maker would *raise* his bid and ask prices, with the ask rising more than the bid to facilitate a wider spread. His higher bid price indicates that he desires to reduce his short exposure, and his higher ask price reflects that he is willing to increase his short position only at a relatively more attractive price.

In Figure 3 we present a diagrammatic representation of bid prices, ask prices, and spreads for a representative stock during two different periods. The period "before" anyone is suffering from SAD is on the left. For simplicity, we assume all market makers have the same information and quote the same bid and ask prices during this period, so everyone's quoted spread is exactly the same as the inside spread. The quoted spread is indicated by the solid line in two-dimensional space, with vertical distance representing price: the ask price is above (*i.e.,* exceeds) the midprice, which in turn exceeds the bid price. The vertical distance between the ask and the bid represents the spread, both quoted and inside in this case.

The period denoted "after," shown to the right of the dotted line, depicts the period when some market makers are suffering from SAD and consequently feeling depressed and experiencing higher risk aversion. (For the sake of simplicity, we assume the SAD-affected market makers hold long inventory positions, though we show below that the implications for inside spreads are invariant to whether market makers hold long, short, or a mix of long and short positions.) About ten percent of the population suffers from the medical condition of SAD, and while more may suffer from sub-clinical forms of seasonal depression, it is probably fair to assume that the majority of market makers do not suffer from severe depression due to SAD. A market maker unaffected by SAD would likely have no reason to revise his bid or ask price. Thus the quoted spread of the market maker unaffected by SAD is identical to his "before" quote. (Again, this quote is also depicted with a solid vertical line.) A market maker who suffers from SAD, however, might lower his bid and ask prices. His choice to reduce his bid price would arise because with his now-higher degree of risk aversion, he is willing to buy the risky asset only at a lower price. The decision to reduce his ask price means he can more quickly liquidate risky positions. Dropping the bid more than the ask would be consistent with him now demanding more compensation for holding risky positions and would lead to the widening of his quoted spread. His lower bid and ask prices are shown with the diagonal-striped line. With some market makers having left their quotes unchanged and others having adjusted their quotes to be lower and their spreads to be wider, the end result is a *narrower inside spread*, as depicted by the short vertical line with horizontal stripes. (The end result is an inside quote representing the bid of one dealer and the ask of another. As discussed by Stoll, 1989, and many others, the inside quote need not necessarily be composed of the bid and ask of a single dealer.)

If instead of assuming the SAD-affected market maker holds long inventory we were to assume he held short inventory, his bid and ask price would both *rise* instead of falling, which would still result in a narrower inside spread than would be observed in absence of SAD. Likewise, if some SAD-affected market makers are long while others are short, some would drop their bid and ask prices while others would raise their bid and ask prices, and the end result would still be a narrower inside spread.

In short, we hypothesize that during autumn some market makers change their bid and ask prices while simultaneously widening the spreads, and then at some point before the end of winter they revert their bid and ask prices while narrowing their spreads. The implication of this hypothesis is that we should observe opposite movements in inside versus quoted spreads during the fall and winter periods. Above, we saw evidence of seasonal patterns in quoted spreads consistent with this hypothesis; we turn now to inside spreads.

B Inside Spreads Data

NYSE firms in effect have only a single market maker, the specialist. To test the SAD hypothesis more fully, however, we need inside spreads which are defined by the interaction of the quotes of more than one market maker. Thus, we employ inside spread data for stocks traded on Nasdaq. As discussed by Wahal (1997), the Nasdaq National Market now allows a dealer who wishes to make a market in a security to begin doing so within a day of registration. This low barrier to entry makes for a fairly competitive dealer market.

We calculate the inside spread for a given Nasdaq stock, i, using the best bid and ask prices at market closing on day t, $Pbestbid_{i,t}$ and $Pbestask_{i,t}$. Then the percentage inside spread, ISpread, is calculated as:

$$ISpread_{i,t} = \frac{(Pbestask_{i,t} - Pbestbid_{i,t})}{(Pbestask_{i,t} + Pbestbid_{i,t})/2}. \tag{4}$$

By using inside spreads at close, we benefit from the point raised by Wahal (1997) that closing quotes more likely reflect competitive conditions since Nasdaq quotes are at their narrowest point of the trading day at close (an intraday regularity shown by Chan, Christie, and Schultz, 1995).

Summary statistics on the inside spreads data and other variables we employ from the Nasdaq dataset are provided in Panel B of Tables 1 and 2. The time period we consider overlaps exactly with the NYSE data we have already discussed. Consider first Table 1. We see that over this 1993 - 2006 time period, there are more than twice as many firm-day observations for Nasdaq than there are for NYSE. The average Nasdaq bid and ask prices are around \$12.50 and \$12.75 respectively, and the average inside spread is about 4.6 percent. Relative to the NYSE data in Panel A, the Nasdaq prices are lower on average. On a percentage basis, Nasdaq inside spreads are much wider than even quoted spreads from the NYSE, consistent with the relatively smaller, risker nature of most Nasdaq firms. The average daily return for the Nasdaq firms in our sample is over 0.1 percent. There are, on average, more than 25 million shares outstanding. The average daily volume of about \$7 million is lower than for NYSE firms. The average daily return variance and average daily turnover are much higher than for NYSE firms, at about 0.4 percent and 0.8 percent respectively. The average Nasdaq firm has about 16 market makers, ranging from a low of zero to a high of 120.[15] Turning to Table 2, Panel B provides summary statistics on the Nasdaq inside spread deciles, formed on the basis of the previous month's market capitalization. Like the quoted spreads in Panel A, the average inside spreads are largest for Decile 1 (the smallest firms) and decline monotonically through to Decile 10. Average volume declines through the deciles. Once again, the average detrended variance values for each decile are close to 1 by construction, though average *raw* variance (not reported) is highest for Decile 1 and declines monotonically through to Decile 10, as expected. Firms in Decile 1 have, on average, the lowest number of market makers, a figure which rises monotonically through to Decile 10. Unlike the NYSE quotes spreads, Nasdaq inside spreads do not exhibit a strong unconditional seasonal cycle. It is to the *conditional* evidence of seasonality in inside spreads that we now turn.

[15] In the very small number of cases where we had valid bid and ask data but the recorded number of market makers was zero, we kept the observation in our sample. Our results are not sensitive to the inclusion of these observations. In practice, the vast majority of firms have at least two market makers. Nasdaq Marketplace Rule 4310(c)(1) indicates "For initial inclusion, the issue shall have three registered and active market makers, and for continued inclusion, the issue shall have two registered and active market makers, one of which may be a market maker entering a stabilizing bid." If a firm has less than two market makers for a period of 10 days or more, the firm risks having its shares delisted.

C Regression Analysis

We use GMM to jointly estimate a set of regressions for the inside spread deciles (10 equations in all).[16] The inside spread equations are:

$$\begin{aligned} ISpread_{i,t} &= \alpha_i + \mu_{Incidence \cdot \sigma_i} Incidence_t \cdot \sigma_{I,i,t-1} + \mu_{Volume_i} Volume_{I,i,t-1} \\ &+ \mu_{Turnover_i} Turnover_{I,i,t-1} + \mu_{\sigma_i^2} \sigma^2_{I,i,t-1} + \mu_{OddEighths} D_t^{OddEighths} \\ &+ \mu_{MM_i} MM_{i,t} + \mu_{Jan} D_{i,t}^{Jan} + \mu_{Q3} D_{i,t}^{Q3} + \mu_{Q4} D_{i,t}^{Q4} + \epsilon_{it}. \end{aligned} \tag{5}$$

All of the variables appearing in the quoted spread equations are as previously defined. For the Nasdaq inside spread equations, several of the variables are identical to the variables used in the NYSE quoted spread equations, including $Incidence_t$, D^{Jan}, D^{Q3}, and D^{Q4}. New variables in the inside spread equations include the average closing inside spread for firms in Nasdaq decile i on day t ($ISpread_{i,t}$, defined in Equation (4) above), $MM_{i,t}$, which is the average number of market makers across firms in each of the inside spread deciles (in accordance with the theory that more dealers should lead to narrower spreads; for instance see Stoll, 1978a), and $D_t^{OddEighths}$, which is a dummy variable that equals zero for dates prior to May 27 1994 and zero otherwise (to control for the narrowing of spreads that occurred after Christie and Schultz, 1994, observed market makers were avoiding odd-eighth quotes). The variables $Volume_{I,i,t-1}$, $Turnover_{I,i,t-1}$, and $\sigma^2_{I,i,t-1}$ used in the inside spread equations (with an 'I' subscript) are calculated based on Nasdaq data analogously to the construction of the NYSE counterpart variables. We calculate the volatility-interacted incidence series, $Incidence_t \cdot \sigma_{I,t-1}$, for the inside spread deciles by interacting the incidence variable with the appropriate Nasdaq-decile volatility measure. Our results are very similar if instead of using the volatility-interacted incidence variable, we use the non-interacted incidence variable, though again the statistical precision of our estimate of the influence of SAD on spreads is sharpened with use of the volatility-interacted incidence variable.

[16] Results are similar if instead we estimate the 10 inside spread equations and 10 quoted spread equations jointly as a system of 20 equations, though results based on the system of 20 equations are most statistically significant due to the higher power that results from exploiting the covariance across the NYSE and Nasdaq markets. We opt to present the results based on the 10 inside spread equations instead of the 20 jointly estimated inside and quoted spread equations in part due to the fact that results based on the set of 10 are more conservative. Furthermore, presenting the set of 10 inside spreads is more efficient in terms of space. Results based on the jointly estimated set of 20 equations are available on request.

Results appear in Table 5, which has the same layout as Tables 3 and 4. In contrast to our earlier results based on quoted spreads, for inside spreads we expect to find a *negative* coefficient on the volatility-interacted incidence coefficient. This is precisely what we find; the estimate is negative and significant for all deciles. That is, while quoted spreads are wider during periods when individuals suffer from SAD, inside spreads are narrower. The economic magnitude of this effect amounts to a narrowing of inside spreads by 40 to 50 basis points for small deciles and just a few basis points for large deciles. Again, these are peak effects based on multiplying a given decile's volatility-interacted incidence coefficients by the value of $Incidence_t$ at its maximum in December. In terms of joint statistical significance, the bottom portion of the table contains a χ^2 test statistic which tests the null that all ten volatility-interacted $Incidence_t \cdot \sigma_{I,i,t-1}$ coefficient estimates are jointly equal to each other across the deciles. The hypothesis is strongly rejected.

The fact that quoted and inside spreads move in opposite directions during specific seasons of the year is perhaps a counter-intuitive result. The finding can be explained, however, by seasonally changing risk aversion among market makers. Figure 3 shows that if, during the autumn, some SAD-affected long-inventory market makers drop their bid and ask prices while simultaneously widening the spreads, and then at some point before the end of winter they raise their bid and ask prices while narrowing their spreads, the implication is opposite movements in inside versus quoted spreads during the fall and winter period. Similar implications hold for quoted spreads and inside spreads if market makers hold short inventories or a mix of long and short inventories.

V Discussion

Having documented what some may consider surprising findings about the seasonal behavior of spreads, we turn now to a discussion of reasonable questions and concerns, including issues relating to whether individuals who work indoors should be immune to the effects of SAD, whether market makers may be less prone to SAD perhaps due to their relatively high education and income levels, whether SAD-affected market makers would be less likely to survive (financially) as market makers, and other general questions about the plausibility of the risk aversion hypothesis we consider.

We begin with the question of whether the seasonal differences we show in inside versus quoted spreads arise simply due to differences between the NYSE market (where we obtain our quoted spreads) and the Nasdaq market (where we obtain our inside spreads). As noted in Section I above when we first introduced our data, we performed unreported robustness checks using Nasdaq intraday quotes data (obtained from the Nastraq database). Analysis of these Nasdaq intraday quotes confirm that the seasonal widening of quotes we observe in the NYSE closing quoted spreads data is also observed in the Nasdaq intraday quoted spreads data. That is, while we obtain a negative coefficient on the incidence variable for Nasdaq closing inside spreads, we obtain a *positive* coefficient on the incidence variable for Nasdaq intraday quoted spreads, just as we obtain a positive coefficient on the incidence variable for NYSE closing quoted spreads. Our findings with respect to volume, variance, and turnover was consistent with economic theory. In the interest of brevity, we elected to omit detailed results based on the intraday Nasdaq quotes.[17]

A valid question is whether people who work indoors, such as Nasdaq market makers, are immune to the effects of SAD. Goetzmann and Zhu (2005) demonstrate that weather effects such as cloud cover have no influence on NYSE specialists' quotes, pointing to the fact that NYSE specialists work in a windowless environment and hence should be mostly unaffected by the outside weather except to the extent that they are exposed to the weather on their way to or from work. The medical condition of Seasonal Affective Disorder arises due to reduced exposure to daylight, which is independent of weather.[18] Daylight is literally a function

[17]For the interested reader, a summary of the approach we adopted in analyzing the intraday quotes (and the complications thereof) is as follows. First, well-known intraday patterns in spreads, volume, and other variables dictated that we choose a particular period during the day upon which to conduct our analysis. While the bulk of our analysis focused on quotes from on the last hour of the trading day, robustness tests indicated that our findings were similar for other one-hour periods of the day. Second, at all points of the day, unrepresentative quotes are fairly common in the Nastraq series (that is, it is common to find exceptionally wide quotes that do not seem typical of the day's trading activity, analogous to the non-representative NYSE closing quotes data that CRSP describes as taking considerable effort to eliminate from their data series.) Attempts to control for this feature of the intraday quotes data without making arbitrary spot-cleaning choices led us to consider *median* intraday quotes, though our findings were similar when we considered mean quotes. Third, the Nasdaq intraday quotes data are available only over a shorter time period, starting in 1999, relative to the CRSP closing quote series. This short time series led to some sensitivity of results to model specification (such as choice of number of HAC lags for GMM estimation) and therefore influenced our choice to rely on NYSE closing quotes which are available over a longer period (a period that mirrors the availability of Nasdaq closing inside spreads).

[18]See Kamstra, Kramer, and Levi (2003) for citations to papers in the medical literature which establish

of the earth's position relative to the sun, and hours of light are calculated as the time between sunrise and sunset, independent of weather conditions. During the fall and winter seasons, when hours of daylight are diminished, people in general have fewer opportunities to be exposed to direct light than they do in the spring and summer. According to the medical literature, for people prone to SAD who work indoors, the impact of the reduced daylight through the fall and winter is at least equivalent to that for SAD sufferers who work outdoors, and may even be more severe. (See Wirz-Justice *et al.*, 1992, and Magnusson and Stefansson, 1993, for clinical evidence.) Thus, the fact that market makers work indoors would not seem sufficient to make them invulnerable to the effects of SAD.

An additional question is whether people who hold professional jobs, people who are relatively wealthy, or people who have relatively high incomes are perhaps less likely to suffer from seasonal depression than others. The evidence suggests that if anything, higher socioeconomic status is associated with a greater risk of seasonal depression. Medical research does suggest that low socioeconomic status may be associated with a higher disposition to non-seasonal depression. (See Lynch *et al.*, 1997, for example.) This association does not seem to apply to seasonal depression, however. For instance, Blazer *et al.* (1998) show that people in high-income families are much more likely to suffer from SAD than those in low-income families, and a study conducted in Finland by Saarijarvi *et al.* (1999) finds that higher levels of education are associated with a higher likelihood to suffer from SAD. In light of these findings, market makers would seem to be at least as likely as the rest of the population to experience the sort of seasonally varying risk aversion we investigate here.

Still another possible challenge to our findings is whether a dealer with SAD would be eventually identified and exploited by other market participants due to the seasonal predictability of his actions. A SAD-affected market maker may change his bid and ask prices during seasons when he is more risk averse, but in practice market makers change their prices for any number of reasons, and there is no reason to believe that other market participants would conclude SAD is behind any particular dealer's quote change at any given point in time. A long-inventory SAD-affected market maker's lower bid price would

that SAD arises due to seasonal changes in daylight, as opposed to seasonal changes in weather conditions such as cloudiness or precipitation.

discourage clients from selling to him, and his lower ask price would encourage clients to buy from him, but this is precisely the long-inventory market maker's goal when he experiences an increase in his risk aversion: he wishes to reduce his inventory. In addition, as he reduces his inventory, he approaches the point at which the risk level of his new portfolio is exactly consistent with the new price level. Similarly, buyers of his shares initially take the lower price as a favorable shift in the tradeoff between expected return and risk. However, as these buyers purchase more shares (and consequently add risk to their portfolios), they approach the point at which the higher expected return exactly compensates them for the added risk. When the SAD-influenced market maker has reduced his inventory sufficiently and the rest of the market has increased its holdings, SAD-driven trading subsides, at least until the market maker experiences another shift in his risk aversion, or until the quote of another SAD-affected market maker arrives.

How likely is the arrival of the quote of another SAD-affected market maker, given the average Nasdaq firm only has 16 market makers? The medical literature suggests that roughly ten percent of the population suffers from SAD, with additional numbers suffering from the milder condition of winter blues. Thus it seems reasonable to expect that the majority of Nasdaq stocks have at least one or two market makers who might experience seasonal depression and that many stocks in each decile will be affected accordingly. If SAD starts to increase individuals' risk aversion at different points through the fall, then the influence of SAD on spreads can persist throughout the season. All that is required is a stream of SAD-affected market participants over time – which is consistent with the observation in the medical literature that the onset of SAD occurs at different times in the fall for different people. The same outcome could be observed if individuals who suffer from SAD experience a *progressive* increase in risk aversion through the fall. Likewise, the medical literature suggests that the effects of SAD dissipate at different points in the winter or spring for different individuals, thus spreads may continue to exhibit the impact of SAD until most or all SAD-influenced individuals have recovered. Again, the same outcome is possible if SAD-sufferers experience a gradual reduction in risk aversion as daylight increases.

Another possible criticism is that during periods when SAD is evident, a SAD-affected market maker might leave the market entirely. As mentioned above, a Nasdaq market maker who stops making a market in a given stock is required to wait 20 days before he resumes trading (see Harris, 2001, page 511). Thus a SAD-affected market maker who is uninterested in trading would likely widen his spread to reduce the likelihood of attracting a trading counterparty rather than discontinue making a market entirely.

VI Robustness Checks

We conducted a wide range of (unreported) robustness checks, all of which are available from the authors on request. Results suggest that our findings are robust to a wide variety of changes. For example, we considered quintiles instead of deciles, we modified the model to include dummies for day of the week or effects from lagged returns, we used a dummy variable for the second half of the year instead of individual third and fourth quarter dummies, we considered a dummy for the third quarter (summer) alone, we completely excluded the quarterly dummy variables and/or the January dummy from the estimation, and we included a dummy for the second quarter. If enough monthly dummy variables are introduced into the regression, multicollinearity reduces the statistical significance of the effect of SAD incidence on spreads, but the magnitude of the effect is largely unchanged.

Additionally, inference is unaffected by monotonic transformations of the way we define many of the explanatory variables, including volume, turnover, and variance. Our findings are unchanged if we control directly for autocorrelation by including 6 lags of the dependent variable as regressors (sufficient to produce white noise) residuals instead of using Newey West standard errors, and our findings are also unchanged if we increase the number of Newey West HAC lags (from 2 to 6) used to calculate standard errors in our GMM estimation.

Nasdaq closing bid-ask spreads are available back to the early-to-mid 1980s.[19] Our findings with respect to the SAD effect are the same if we employ a longer sample of Nasdaq closing inside spreads data dating back to the 1980s; for the sake of symmetry with the NYSE sample period, we report results for the shorter period only. Finally, we also found our con-

[19]CRSP provides Nasdaq data starting as early as 1982, but the bid and ask price data are sparse until the beginning of 1984.

clusions were unchanged by considering value-weighted deciles instead of equal-weighted, considering median or mean intraday quoted spreads over various one-hour intervals during the day (first hour of trading, last hour of trading, *etc.*) instead of closing spreads, estimating the 10 inside spread deciles and 10 quoted spread deciles together as a system of 20 equations instead of separately as two independent sets of 10 equations, and restricting our study to stocks trading at prices greater than or equal to $5 instead of including all stocks. Results based on value-weighted deciles and based on excluding stocks with prices less than $5 are most comparable to the results we presented above for deciles of larger-sized firms.

VII Conclusions

Seasonal variation in bid-ask spreads, as well as variation conditional on inventory cost changes, adverse selection events, and competition among market makers, has been extensively documented in past studies. Recent work by Kamstra, Kramer and Levi (2003, 2007) detects strong seasonal patterns in equity and Treasury returns, perhaps as a consequence of time-varying risk aversion due to seasonal depression. We consider whether there is evidence of time-varying risk aversion influencing bid-ask spreads. We find that while individual NYSE dealer quotes (quoted spreads) widen during the fall and winter seasons, Nasdaq inside spreads narrow during that period. These findings are consistent with some market makers experiencing seasonal changes in risk aversion that align with the timing of seasonal depression associated with SAD. The impact of SAD on spreads, both inside and quoted, appears greater for smaller firms, with the magnitude of the effect varying monotonically across deciles. The economic impact of this seasonal effect is such that quoted spreads widen by about 20 basis points during the period of maximum possible impact (the period when daylight is most diminished) and inside spreads narrow by about 20 basis points, relative to the unconditional averages of 180 and 460 basis points respectively. The finding of opposing seasonal patterns in individual dealer spreads versus inside spreads has clear implications for the timing of trades by liquidity traders and discretionary traders. We rule out several alternative explanations for and interpretations of our results, and our conclusions are insensitive to a variety of robustness checks.

References

Blazer, D.G., R.C. Kessler, and M.S., Swarz, 1998, Epidemiology of recurrent major and minor depression with a seasonal pattern. *British Journal of Psychiatry* 172, 164-167.

Chan, K. C., William G. Christie, and Paul H. Schultz, 1995, Market Structure and the Intraday Pattern of Bid-Ask Spreads for NASDAQ Securities, *Journal of Business* 68, 35-60.

Christie, William G. and Paul H. Schultz, 1994, Why Do NASDAQ Market Makers Avoid Odd-Eighth Quotes? *Journal of Finance* 49(5), 1813-1840.

Clark, R., J. McConnell, and M. Singh, 1992, Seasonalities in NYSE Bid-Ask Spreads and Stock Returns in January, *Journal of Finance* 47(5), 1999-2014.

Fortin, R., R. Grube, and O. Joy, 1989, Seasonality in NASDAQ Dealer Spreads, *Journal of Financial and Quantitative Analysis* 3(24), 395-407.

Goetzmann, William N. and Ning Zhu, 2005, Rain or Shine: Where is the Weather Effect? *European Financial Management* 11(5), 559-578.

Hansen, Lars Peter, 1982, Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica* 50, 1029-1054.

Harris, Larry, 2003, Trading and Exchanges. Oxford University Press: New York, NY.

Ho, Thomas S.Y. and Hans R. Stoll, 1981, Optimal Dealer Pricing Under Transactions and Return Uncertainty, *Journal of Financial Economics* 9, 47-73.

Ho, Thomas S.Y. and Hans R. Stoll, 1983, The Dynamics of Dealer Markets Under Competition, *Journal of Finance* 38(4), 1053-1074.

Hong, Harrison and Jialin Yu, 2007, Gone Fishin': Seasonality in Trading Activity and Asset Prices, Princeton University Manuscript.

Kamstra, Mark J., Lisa A. Kramer and Maurice D. Levi, 2003, Winter Blues: Seasonal Affective Disorder (SAD) and Stock Market Returns, *American Economic Review* 93(1), 324-343.

Kamstra, Mark J., Lisa A. Kramer and Maurice D. Levi, 2007, Opposing Seasonalities in Treasury versus Equity Returns, University of Toronto Manuscript, available at SSRN: http://ssrn.com/abstract=1076644.

Lam, Raymond W., 1998b, Seasonal Affective Disorder: Diagnosis and Management, *Primary Care Psychiatry* 4, 63-74.

Lynch, J.W., G.A. Kaplan, and S.J. Shema, 1997, Cumulative impact of sustained economic hardship on physical, cognitive, psychological and social functioning, *New England Journal of Medicine* 337(26), 1889-1895.

Magnusson, A. and J.G. Stefansson, 1993, Prevalence of seasonal affective disorder in Iceland, *Archives of General Psychiatry* 50, 941-951.

Newey, Whitney K. and Kenneth D. West, 1987, A Simple, Positive, Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

Saarijarvi, S., H. Lauerma, H. Helenius, and S. Saarilehto, 1999, Seasonal affective disorders among rural Finns and Lapps, *Acta Psychiatrica Scandinavica* 99, 95-101.

Stoll, Hans R., 1978a, The Supply of Dealer Services in Securities Markets, *Journal of Finance* 33(4), 1133-1151.

Stoll, Hans R., 1978b, The Pricing of Security Dealer Services: An Empirical Study of NASDAQ Stocks, *Journal of Finance* 33(4), 1153-1172.

Stoll, Hans R., 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *Journal of Finance* 44(1), 115-134.

Wahal, Sunil, 1997. Entry, Exit, Market Makers, and the Bid-Ask Spread, *Review of Financial Studies* 10(3) 871-901.

Wirz-Justice, A., K. Krauchi, P. Graw, J. Schulman, and H. Wirz, 1992, Seasonality in Switzerland: an epidemiological survey, *4th Annual Meeting on Light Treatment and Biological Rhythms*, Bethesda, Maryland, USA: Society for Light Treatment and Biological Rhythms, 33.

Young, Michael A., Patricia M. Meaden, Louis F. Fogg, Eva A. Cherin, and Charmane I. Eastman, 1997, Which Environmental Variables are Related to the Onset of Seasonal Affective Disorder? *Journal of Abnormal Psychology* 106(4), 554-562.

Table 1: Summary Statistics for Pooled Data

We provide summary statistics on daily firm-level data pooled across firms over the January 4 1993 to December 29 2006 time period. Data are obtained from CRSP. Panel A contains NYSE data, and Panel B contains Nasdaq data. Percentage quoted spreads are calculated according to Equation (1) using closing bid and ask prices (for which we provide summary statistics as well). Daily returns are calculated using closing prices (which are not reported). Shares outstanding are reported in thousands. Dollar volume is calculated as the product of a given stock's closing price and its share volume (in millions), and we also report the natural logarithm of that figure. Daily percentage variance is calculated as squared returns. Percentage turnover is calculated as a given stock's share volume divided by its number of shares outstanding, multiplied by 100. In Panel B, the number of market makers is the reported number of market makers covering a particular stock on a given day. Note that in each panel, the largest number of observations is observed for bids, asks, and spreads. For other variables, we tolerate missing values because when we form deciles we are able to calculate decile averages by relying on non-missing values from other firms in the decile. Robustness checks confirm that our findings are unchanged if we exclude all observations that have a missing value for any variable in our model.

Panel A: NYSE Data 1993-2006

Variable	N	Mean	Std. Dev.	Min	Max	Skew	Kurt
Quoted Spread (%)	5,653,454	1.811	2.95	$<$0.01	199.98	11.188	348.32
Bid ($)	5,653,454	27.983	24.55	0.01	994.54	9.672	253.99
Ask ($)	5,653,454	28.292	24.65	0.03	996.77	9.652	252.56
Daily Return (%)	5,653,438	0.062	2.85	-95.40	1,290.3	19.211	7,659.7
Shares Outstanding (000s)	5,653,454	122,412	380,432	1.00	1.11×10^7	12.084	222.19
Ln Volume (ln $millions)	5,587,726	0.746	2.43	-12.02	9.17	-0.371	0.01
Volume ($millions)	5,587,726	19.064	66.30	$<$0.01	9600.1	15.867	684.88
Return Variance (%)	5,652,034	0.082	1.50	$<$0.01	800.02	508.14	269,598
Turnover (%)	5,587,726	0.535	4.97	$<$0.01	6240.0	535.72	512,696

Panel B: Nasdaq Data 1993-2006

Variable	N	Mean	Std. Dev.	Min	Max	Skew	Kurt
Inside Spread (%)	12,810,305	4.620	6.84	$<$0.01	199.75	5.048	47.19
Bids ($)	12,810,305	12.479	17.35	0.01	1142.5	10.746	351.47
Asks ($)	12,810,305	12.755	17.54	0.02	2000.0	10.942	367.10
Daily Return (%)	12,809,990	0.132	6.38	-95.65	1595.5	8.366	919.21
Shares Outstanding (000s)	12,810,305	25,912	138457	1.00	1.09×10^7	39.807	2,098.7
Ln Volume (ln $millions)	11,932,712	-1.513	2.70	-13.37	9.63	0.051	-0.18
Volume ($millions)	11,932,712	7.012	67.26	$<$0.01	15281	41.407	3,317.5
Return Variance (%)	12,801,367	0.399	2.79	$<$0.01	1162.2	225.27	74,012
Turnover (%)	11,932,713	0.800	3.39	$<$0.01	2533.0	146.93	56,739
# Market Makers	12,810,305	16.156	12.46	0.00	120.00	1.973	5.74

Table 2: Summary Statistics for Deciles

We provide summary statistics based on daily data for both the NYSE stocks and the Nasdaq stocks we consider, with data obtained from CRSP. For each market, we form deciles on the basis of each stock's lagged average monthly market capitalization. The raw daily series are from CRSP and run from January 4 1993 through December 29 2006, yielding a total of 3527 daily observations. The summary statistics we present for each decile, by market, include the mean, standard deviation, minimum, maximum, skewness, and excess kurtosis. Panel A contains the NYSE deciles' summary statistics. Quoted spreads are calculated for each decile by taking the average of the percentage quoted spreads, as defined in Equation (1) across all the stocks in the decile. Lagged log dollar volume is computed for each decile as follows: We take each stock's closing price for the previous day times its share volume for the previous day (in millions), calculate the average across all stocks in the decile, then take the natural logarithm of that figure. To calculate the lagged return variance for a particular decile, we first calculate the previous month's average squared return for each stock in the decile. Then we take the average of these individual stock variances across all stocks in the decile. Finally, we detrend the decile variance by dividing by the decile's variance averaged over the past 252 trading days, and we multiply by 100. Lagged turnover is calculated for each decile by taking a given stock's share volume for the previous day divided by its number of shares outstanding for the previous day, averaging across all stocks in the decile, and multiplying by 100.

Panel B contains the Nasdaq summary statistics. The number of market makers for each decile is defined as the number of market makers covering a stock on a given day, averaged across all stocks in the decile. Inside spreads are calculated for each decile as follows: For each stock we calculate the percentage inside spread, defined in Equation (4), then we take the average across all stocks in the decile. Lagged log volume, lagged variance, and lagged turnover are defined as for the NYSE data.

Panel A: NYSE Data 1993-2006

Decile	Variable	Mean	Std. Deviation	Min	Max	Skew	Kurt
Decile 1	Quoted Spread (%)	5.338	3.11	0.62	34.60	1.142	6.98
	Ln Volume (ln $millions)	-1.707	0.64	-5.62	0.78	-0.555	2.32
	Volume ($millions)	0.220	0.14	<0.01	2.19	2.273	13.64
	Turnover (%)	0.847	1.51	0.04	49.00	13.997	337.72
	Detrended Return Variance (%)	0.985	0.99	0.18	19.78	11.776	168.43
Decile 2	Quoted Spread (%)	2.882	2.11	0.23	24.32	2.958	21.72
	Ln Volume (ln $millions)	-0.611	0.74	-4.53	1.47	-0.118	1.71
	Volume ($millions)	0.716	0.60	0.01	4.35	1.821	3.14
	Turnover (%)	0.436	0.17	0.05	1.66	1.357	3.57
	Detrended Return Variance (%)	0.995	0.39	0.36	4.23	2.382	9.64
Decile 3	Quoted Spread (%)	2.169	1.43	0.14	15.45	1.054	5.49
	Ln Volume (ln $millions)	0.114	0.76	-4.11	2.13	0.144	1.28
	Volume ($millions)	1.518	1.36	0.02	8.41	1.839	2.83
	Turnover (%)	0.458	0.19	0.04	2.00	1.201	2.08
	Detrended Return Variance (%)	1.007	0.38	0.25	4.47	2.201	8.61
Decile 4	Quoted Spread (%)	1.807	1.18	0.10	17.63	1.047	10.24
	Ln Volume (ln $millions)	0.640	0.79	-2.58	3.68	0.608	0.55
	Volume ($millions)	2.717	3.12	0.08	39.63	4.696	37.28
	Turnover (%)	0.476	0.21	0.08	1.60	1.121	0.65
	Detrended Return Variance (%)	1.010	0.36	0.41	4.31	2.390	10.41
Decile 5	Quoted Spread (%)	1.530	0.94	0.09	6.59	0.009	0.07
	Ln Volume (ln $millions)	1.161	0.78	-1.90	4.50	0.791	1.06
	Volume ($millions)	4.651	6.38	0.15	90.09	6.381	56.02
	Turnover (%)	0.516	0.23	0.08	1.63	1.110	0.91
	Detrended Return Variance (%)	1.010	0.37	0.44	4.96	2.570	13.48
Decile 6	Quoted Spread (%)	1.360	0.83	0.08	7.08	-0.158	0.03
	Ln Volume (ln $millions)	1.639	0.77	-3.77	4.76	0.695	1.17
	Volume ($millions)	7.357	9.05	0.02	116.34	4.966	34.41
	Turnover (%)	0.548	0.24	0.02	2.33	1.069	1.28
	Detrended Return Variance (%)	1.011	0.34	0.30	2.52	1.502	3.47
Decile 7	Quoted Spread (%)	1.217	0.74	0.07	3.91	-0.321	-1.09
	Ln Volume (ln $millions)	2.092	0.73	-2.93	5.28	0.776	1.95
	Volume ($millions)	11.334	15.50	0.05	197.13	6.428	51.07
	Turnover (%)	0.544	0.21	0.03	1.40	0.671	-0.18
	Detrended Return Variance (%)	1.014	0.36	0.16	2.96	1.829	5.31
Decile 8	Quoted Spread (%)	1.072	0.67	0.06	3.23	-0.121	-0.85
	Ln Volume (ln $millions)	2.614	0.74	-2.31	5.61	0.641	1.54
	Volume ($millions)	19.049	24.78	0.10	273.37	5.948	43.97
	Turnover (%)	0.555	0.22	0.05	1.44	0.640	-0.15
	Detrended Return Variance (%)	1.015	0.37	0.35	3.37	1.833	6.08
Decile 9	Quoted Spread (%)	0.906	0.59	0.05	3.00	0.291	0.11
	Ln Volume (ln $millions)	3.297	0.71	-2.48	6.09	0.368	1.55
	Volume ($millions)	36.037	37.86	0.08	441.08	4.695	30.61
	Turnover (%)	0.545	0.20	0.03	1.47	0.560	-0.24
	Detrended Return Variance (%)	1.016	0.36	0.37	2.56	1.263	2.42
Decile 10	Quoted Spread (%)	0.706	0.50	0.04	2.71	0.877	1.64
	Ln Volume (ln $millions)	4.553	0.70	-2.96	6.62	-0.617	3.02
	Volume ($millions)	118.38	80.62	0.05	748.94	2.226	10.19
	Turnover (%)	0.414	0.13	0.01	1.12	0.455	0.18
	Detrended Return Variance (%)	1.018	0.38	0.33	2.54	1.191	1.85

Panel B: Nasdaq Data 1993-2006

Decile	Variable	Mean	Std. Deviation	Min	Max	Skew	Kurt
Decile 1	Inside Spread (%)	12.513	6.46	2.01	28.48	0.071	-1.11
	Ln Volume (ln $millions)	-3.101	0.92	-5.25	1.03	1.023	1.27
	Volume ($millions)	0.081	0.16	0.01	2.79	7.504	82.17
	Turnover (%)	0.944	0.79	0.22	11.41	4.820	35.33
	Detrended Return Variance (%)	0.956	0.42	0.29	4.44	2.968	16.06
	# of Market Makers	9.667	2.30	6.90	16.81	1.741	1.70
Decile 2	Inside Spread (%)	7.515	3.83	1.19	21.32	-0.010	-1.11
	Ln Volume (ln $millions)	-2.490	0.85	-4.35	1.94	0.939	1.05
	Volume ($millions)	0.135	0.26	0.01	6.94	11.885	221.35
	Turnover (%)	0.586	0.36	0.16	6.87	5.876	66.02
	Detrended Return Variance (%)	0.964	0.33	0.43	2.54	1.961	5.22
	# of Market Makers	10.870	2.73	7.86	19.63	1.753	1.68
Decile 3	Inside Spread (%)	5.663	2.98	0.80	18.54	0.076	-0.95
	Ln Volume (ln $millions)	-1.945	0.81	-4.10	0.67	0.589	-0.35
	Volume ($millions)	0.207	0.22	0.02	1.95	2.707	10.32
	Turnover (%)	0.557	0.25	0.09	2.29	2.143	7.44
	Detrended Return Variance (%)	0.968	0.30	0.46	2.36	1.502	3.14
	# of Market Makers	11.944	3.10	9.19	21.57	1.634	1.38
Decile 4	Inside Spread (%)	4.503	2.47	0.58	14.30	0.111	-1.06
	Ln Volume (ln $millions)	-1.469	0.77	-3.40	1.71	0.496	-0.35
	Volume ($millions)	0.319	0.32	0.03	5.55	3.809	32.96
	Turnover (%)	0.564	0.25	0.11	2.82	2.347	9.92
	Detrended Return Variance (%)	0.965	0.44	0.48	6.09	6.498	60.31
	# of Market Makers	13.320	4.07	9.52	26.13	1.512	0.97
Decile 5	Inside Spread (%)	3.581	2.07	0.40	10.75	0.116	-1.15
	Ln Volume (ln $millions)	-0.966	0.73	-2.96	1.58	0.500	-0.51
	Volume ($millions)	0.509	0.45	0.05	4.86	2.202	7.46
	Turnover (%)	0.595	0.23	0.15	2.99	2.112	8.54
	Detrended Return Variance (%)	0.972	0.31	0.50	2.71	2.083	6.40
	# of Market Makers	14.705	5.02	9.80	29.16	1.301	0.51
Decile 6	Inside Spread (%)	2.884	1.78	0.25	10.92	0.153	-1.14
	Ln Volume (ln $millions)	-0.424	0.75	-2.38	2.30	0.388	-0.77
	Volume ($millions)	0.880	0.76	0.09	10.01	2.161	9.54
	Turnover (%)	0.681	0.26	0.15	4.26	2.509	19.61
	Detrended Return Variance (%)	0.995	0.61	0.41	9.71	8.689	96.58
	# of Market Makers	16.294	5.99	9.89	31.51	1.043	-0.08
Decile 7	Inside Spread (%)	2.327	1.57	0.17	8.32	0.307	-1.20
	Ln Volume (ln $millions)	0.134	0.74	-2.21	2.57	0.289	-0.65
	Volume ($millions)	1.515	1.27	0.11	13.00	2.119	7.42
	Turnover (%)	0.773	0.29	0.14	3.81	2.127	10.07
	Detrended Return Variance (%)	0.987	0.30	0.43	2.27	1.540	3.33
	# of Market Makers	18.074	7.10	9.72	35.79	0.778	-0.51
Decile 8	Inside Spread (%)	1.830	1.32	0.14	7.78	0.404	-1.12
	Ln Volume (ln $millions)	0.787	0.73	-1.47	2.64	-0.043	-0.80
	Volume ($millions)	2.830	2.05	0.23	14.05	1.409	2.45
	Turnover (%)	0.914	0.30	0.18	4.74	1.773	10.76
	Detrended Return Variance (%)	0.991	0.32	0.46	2.61	1.944	5.56
	# of Market Makers	20.431	8.60	9.81	39.95	0.543	-0.93
Decile 9	Inside Spread (%)	1.327	1.03	0.11	7.52	0.532	-0.92
	Ln Volume (ln $millions)	1.588	0.75	-0.91	3.31	-0.237	-0.91
	Volume ($millions)	6.334	4.37	0.40	27.28	1.057	1.12
	Turnover (%)	1.086	0.33	0.17	2.80	0.513	0.45
	Detrended Return Variance (%)	0.997	0.33	0.42	2.88	1.953	6.73
	# of Market Makers	23.588	10.24	10.80	44.97	0.309	-1.36
Decile 10	Inside Spread (%)	0.769	0.63	0.07	8.36	1.032	4.82
	Ln Volume (ln $millions)	3.717	0.83	0.99	5.63	-0.385	-0.79
	Volume ($millions)	55.510	40.34	2.68	279.46	1.122	1.32
	Turnover (%)	1.320	0.39	0.24	3.27	0.546	0.55
	Detrended Return Variance (%)	1.002	0.37	0.34	2.79	1.540	3.51
	# of Market Makers	33.292	13.03	15.87	56.79	0.068	-1.66

Table 3: Estimation Results for Quoted Spread Deciles

We report regression results from jointly estimating the following model for the 10 quoted spread deciles in a Hansen (1982) GMM framework:

$$\begin{aligned} QSpread_{i,t} = \alpha_i &+ \mu_{Incidence_i} Incidence_t + \mu_{Volume_i} Volume_{i,t-1} \\ &+ \mu_{Turnover_i} Turnover_{i,t-1} + \mu_{\sigma_i^2} \sigma^2_{i,t-1} \\ &+ \mu_{Jan} D^{Jan}_{i,t} + \mu_{Q3} D^{Q3}_{i,t} + \mu_{Q4} D^{Q4}_{i,t} + \epsilon_{it}. \end{aligned} \quad (2)$$

Variables are defined as follows: $QSpread_{i,t}$ is the average closing quoted spread for firms in decile i on day t, defined in Equation (1) above. $Incidence_t$ is the instrumented daily measure of SAD incidence. $Volume_{i,t-1}$ is the log of decile i's average dollar volume (in millions) at $t-1$. $Turnover_{i,t-1}$ is the average at $t-1$, across all firms in decile i, of share volume divided by shares outstanding, times 100. $\sigma^2_{i,t-1}$ is calculated as follows. First we determine which stocks are in the decile on a given day, then for that group of stocks, we calculate the previous month's average daily variance using squared returns. This yields a daily raw variance series. Next, we detrend the raw variance series by dividing by the raw variance averaged over the past 252 trading days. Finally, we multiply by 100. The result is our (detrended) lagged variance series, in percentage terms. D^{Jan}_t is a dummy for dates in the month of January, D^{Q3}_t is a dummy variable for dates in the third quarter (July through September), and D^{Q4}_t is a dummy variable for dates in the fourth quarter (October through December). The top portion of the table contains parameter estimates and HAC robust t-tests in parentheses. At the bottom the table, we present the value of R^2 for each equation, a χ^2 test for the presence of up to 10 lags of autocorrelation with 10 degrees of freedom, and a χ^2 test for the presence of up to 10 lags of ARCH with 10 degrees of freedom. We also present a Wald χ^2 test statistic, with degrees of freedom in brackets, to test whether the $Incidence_t$ coefficient estimates are jointly statistically different from each other across the quoted spread series. In all cases, one, two, and three asterisks denote significance at the ten, five, and one percent level of significance respectively, based on two-sided tests. The sample period is January 4 1993 through December 29 2006. The regressions were run placing zero weight on the quoted spreads during February 6 through May 18 2001 inclusive, due to the relative lack of availability of representative closing bid and ask data during that period.

Parameter Estimates, T-Tests, and Some Joint Tests Across Equations

	Quoted Spread Decile 1	Quoted Spread Decile 2	Quoted Spread Decile 3	Quoted Spread Decile 4	Quoted Spread Decile 5	Quoted Spread Decile 6	Quoted Spread Decile 7	Quoted Spread Decile 8	Quoted Spread Decile 9	Quoted Spread Decile 10	Joint χ^2 Test (P-value)
α	0.7438***	0.2831***	1.2302***	1.8292***	2.0512***	2.3694***	2.5934***	2.6054***	2.4361***	0.4666***	.
	(8.87)	(4.76)	(32.05)	(74.77)	(122.85)	(170.28)	(179.48)	(190.80)	(177.65)	(21.10)	
$\mu_{Incidence}$	0.7260***	0.3228***	0.1665***	0.1676***	0.1224***	0.1121***	0.0746***	0.0998***	0.0933***	0.1009***	102.7
	(6.31)	(7.38)	(4.70)	(6.44)	(5.42)	(5.98)	(3.90)	(5.76)	(6.05)	(5.85)	(0)
μ_{Volume}	-2.5411***	-1.8167***	-1.4418***	-1.1754***	-1.1552***	-0.9553***	-0.8907***	-0.8463***	-0.6910***	0.0961***	37270.9
	(-94.85)	(-104.76)	(-93.40)	(-92.02)	(-131.67)	(-105.18)	(-112.06)	(-132.75)	(-127.79)	(12.40)	(0)
$\mu_{Turnover}$	-0.0495***	0.5275***	0.6054***	0.1339***	0.5454***	0.1043***	0.1135***	0.4622***	0.5481***	-1.5240***	2846.3
	(-5.30)	(6.15)	(9.44)	(2.89)	(19.72)	(3.70)	(4.32)	(22.87)	(27.91)	(-31.42)	(0)
μ_{σ^2}	-0.0007	1.1458***	0.7504***	0.5764***	0.4734***	0.4354***	0.3796***	0.3355***	0.3463***	0.3595***	7996.9
	(-0.06)	(55.00)	(53.44)	(49.37)	(58.59)	(56.85)	(56.23)	(54.96)	(59.66)	(47.07)	(0)
μ_{Jan}	-0.0479	-0.1407***	-0.0270	-0.0676*	-0.0787***	-0.0019	0.0180	0.0218	0.0920***	0.1181***	145.3
	(-0.34)	(-2.58)	(-0.64)	(-1.96)	(-2.82)	(-0.07)	(0.76)	(0.87)	(3.96)	(5.05)	(0)
μ_{Q3}	-0.2432**	-0.1419***	-0.0540	-0.1262***	-0.1185***	-0.0986***	-0.1235***	-0.0854***	-0.0567***	-0.0589***	143.4
	(-2.09)	(-3.21)	(-1.43)	(-4.72)	(-5.28)	(-5.32)	(-6.37)	(-4.71)	(-3.65)	(-3.51)	(0)
μ_{Q4}	-0.3054***	-0.2942***	-0.1186***	-0.0940***	-0.1069***	-0.1194***	-0.1211***	-0.0591***	-0.0189*	-0.0005	424.1
	(-3.98)	(-10.42)	(-5.25)	(-5.35)	(-7.33)	(-9.68)	(-9.82)	(-5.13)	(-1.83)	(-0.04)	(0)

Diagnostic Statistics

R^2	0.281	0.608	0.613	0.699	0.707	0.733	0.661	0.593	0.495	0.182
χ^2 Test for AR(10)	22771.32***	11576.47***	16283.57***	11798.36***	12484.27***	9395.06***	11686.93***	15750.18***	13651.74***	17369.67***
χ^2 Test for ARCH(10)	1251.1***	346.1***	2290.9***	1366.5***	718.0***	848.3***	982.2***	1479.4***	2010.9***	2963.5***
Economic Impact of Incidence in December	0.700	0.311	0.161	0.162	0.118	0.108	0.072	0.096	0.090	0.097

Joint Equation Diagnostic Statistics

Test:	χ^2 Test (P-Value)
Test for Incidence Coefficients Equal Across All Deciles	83.1 (0)

Table 4: Estimation Results for Quoted Spread Deciles Using Volatility-Interacted Incidence Variable

We report regression results from jointly estimating the following model for the 10 quoted spread deciles in a GMM framework:

$$\begin{aligned} QSpread_{i,t} = {} & \alpha_i + \mu_{Incidence \cdot \sigma_i} Incidence_t \cdot \sigma_{i,t-1} + \mu_{Volume_i} Volume_{i,t-1} \\ & + \mu_{Turnover_i} Turnover_{i,t-1} + \mu_{\sigma_i^2} \sigma_{i,t-1}^2 \\ & + \mu_{Jan} D_{i,t}^{Jan} + \mu_{Q3} D_{i,t}^{Q3} + \mu_{Q4} D_{i,t}^{Q4} + \epsilon_{it}. \end{aligned} \quad (3)$$

Variables are defined as follows: $QSpread_{i,t}$ is the average closing quoted spread for firms in decile i on day t, defined in Equation (1) above. $Incidence_t \cdot \sigma_{i,t-1}$ is the instrumented daily measure of SAD incidence interacted with lagged volatility (defined below). $Volume_{i,t-1}$ is the log of decile i's average dollar volume (in millions) at $t-1$. $Turnover_{i,t-1}$ is the average at $t-1$, across all firms in decile i, of share volume divided by shares outstanding, times 100. $\sigma_{i,t-1}^2$ is calculated as follows. First we determine which stocks are in the decile on a given day, then for that group of stocks, we calculate the previous month's average daily variance using squared returns. This yields a daily raw variance series. Next, we detrend the raw variance series by dividing by the raw variance averaged over the past 252 trading days. Finally, we multiply by 100. The result is our (detrended) lagged variance series, in percentage terms. D_t^{Jan} is a dummy for dates in the month of January, D_t^{Q3} is a dummy variable for dates in the third quarter (July through September), and D_t^{Q4} is a dummy variable for dates in the fourth quarter (October through December). The top portion of the table contains parameter estimates and HAC robust t-tests in parentheses. At the bottom the table, we present the value of R^2 for each equation, a χ^2 test for the presence of up to 10 lags of autocorrelation with 10 degrees of freedom, and a χ^2 test for the presence of up to 10 lags of ARCH with 10 degrees of freedom. We also present a Wald χ^2 test statistic, with degrees of freedom in brackets, to test whether the $Incidence_t \cdot \sigma_{i,t-1}$ coefficient estimates are jointly statistically different from each other across the quoted spread series. In all cases, one, two, and three asterisks denote significance at the ten, five, and one percent level of significance respectively, based on two-sided tests. The sample period is January 4 1993 through December 29 2006. The regressions were run placing zero weight on the quoted spreads during February 6 through May 18 2001 inclusive, due to the relative lack of availability of representative closing bid and ask data during that period.

Parameter Estimates, T-Tests, and Some Joint Tests Across Equations

	Quoted Spread Decile 1	Quoted Spread Decile 2	Quoted Spread Decile 3	Quoted Spread Decile 4	Quoted Spread Decile 5	Quoted Spread Decile 6	Quoted Spread Decile 7	Quoted Spread Decile 8	Quoted Spread Decile 9	Quoted Spread Decile 10	Joint χ^2 Test (P-value)
α	0.9032***	0.3576***	1.2706***	1.8654***	2.0757***	2.3920***	2.6053***	2.6198***	2.4536***	0.4916***	.
	(13.62)	(6.37)	(36.60)	(84.28)	(150.40)	(192.98)	(207.53)	(218.18)	(197.25)	(22.93)	
$\mu_{Incidence \cdot \sigma}$	0.9879***	0.3540***	0.2032***	0.1955***	0.1290***	0.1070***	0.0843***	0.1254***	0.1200***	0.1173***	173.9
	(9.36)	(8.28)	(5.96)	(7.49)	(5.86)	(5.84)	(4.53)	(7.38)	(7.88)	(6.94)	(0)
μ_{Volume}	-2.5092***	-1.8117***	-1.4377***	-1.1723***	-1.1533***	-0.9549***	-0.8909***	-0.8466***	-0.6910***	0.0935***	37840.4
	(-94.90)	(-104.40)	(-93.12)	(-91.39)	(-131.27)	(-105.20)	(-112.06)	(-132.25)	(-126.78)	(12.11)	(0)
$\mu_{Turnover}$	-0.0571***	0.5305***	0.5957***	0.1287***	0.5429***	0.1058***	0.1162***	0.4673***	0.5497***	-1.5071***	2878.9
	(-6.03)	(6.19)	(9.33)	(2.77)	(19.65)	(3.76)	(4.43)	(23.10)	(27.88)	(-31.25)	(0)
μ_{σ^2}	-0.2160***	1.0562***	0.6979***	0.5282***	0.4450***	0.4126***	0.3624***	0.3088***	0.3169***	0.3331***	5923.5
	(-8.48)	(45.28)	(42.70)	(39.79)	(47.82)	(47.09)	(46.42)	(44.42)	(47.97)	(39.90)	(0)
μ_{Jan}	-0.2052	-0.1558***	-0.0454	-0.0835**	-0.0796***	0.0043	0.0155	0.0112	0.0809***	0.1130***	149.3
	(-1.49)	(-2.89)	(-1.12)	(-2.43)	(-2.90)	(0.17)	(0.66)	(0.45)	(3.51)	(4.89)	(0)
μ_{Q3}	-0.1512	-0.1299***	-0.0419	-0.1154***	-0.1156***	-0.0991***	-0.1188***	-0.0744***	-0.0463***	-0.0525***	161.7
	(-1.31)	(-2.98)	(-1.13)	(-4.31)	(-5.18)	(-5.34)	(-6.16)	(-4.12)	(-2.99)	(-3.16)	(0)
μ_{Q4}	-0.3738***	-0.2989***	-0.1275***	-0.1006***	-0.1088***	-0.1181***	-0.1242***	-0.0675***	-0.0274***	-0.0066	379.7
	(-4.97)	(-10.63)	(-5.64)	(-5.68)	(-7.39)	(-9.54)	(-10.01)	(-5.74)	(-2.63)	(-0.52)	(0)

Diagnostic Statistics

R^2	0.287	0.609	0.614	0.7	0.707	0.733	0.662	0.595	0.496	0.183
χ^2 Test for AR(10)	23300.98***	11728.84***	16352.71***	11799.44***	12486.59***	9390.93***	11653.12***	15767.57***	13645.74***	17387.19***
χ^2 Test for ARCH(10)	1253.3***	344.3***	2294.2***	1370.7***	721.0***	850.5***	988.3***	1479.1***	2017.1***	2962.9***
Economic Impact of Incidence in December	0.952	0.341	0.196	0.188	0.124	0.103	0.081	0.121	0.116	0.113

Joint Equation Diagnostic Statistics

Test:	χ^2 Test (P-Value)
Test for Volatility-Interacted Incidence Coefficients Equal Across All Deciles	164.9 (0)

Table 5: Estimation Results for Inside Spread Deciles Using Volatility-Interacted Incidence Variable

We report regression results from jointly estimating the following model for the 10 inside spread deciles in a GMM framework:

$$\begin{aligned} ISpread_{i,t} = {} & \alpha_i + \mu_{Incidence \cdot \sigma_i} Incidence_t \cdot \sigma_{I,i,t-1} + \mu_{Volume_i} Volume_{I,i,t-1} \\ & + \mu_{Turnover_i} Turnover_{I,i,t-1} + \mu_{\sigma_i^2} \sigma^2_{I,i,t-1} + \mu_{OddEighths} D_t^{OddEighths} \\ & + \mu_{MM_i} MM_{i,t} + \mu_{Jan} D_{i,t}^{Jan} + \mu_{Q3} D_{i,t}^{Q3} + \mu_{Q4} D_{i,t}^{Q4} + \epsilon_{it}. \end{aligned} \tag{5}$$

Variables are defined as follows: $ISpread_{i,t}$ is the average closing inside spread for firms in decile i on day t, defined in Equation (4) above. $Incidence_t \cdot \sigma_{t-1}$ is the instrumented daily measure of SAD incidence interacted with lagged volatility (defined below). $Volume_{I,i,t-1}$ is the log of the Nasdaq decile i average dollar volume (in millions) at $t-1$. $Turnover_{I,i,t-1}$ is the average at $t-1$, across all Nasdaq firms in decile i, of share volume divided by shares outstanding, times 100. $\sigma^2_{i,t-1}$ is calculated as follows. First we determine which stocks are in the decile on a given day, then for that group of stocks, we calculate the previous month's average daily variance using squared returns. This yields a daily raw variance series. Next, we detrend the raw variance series by dividing by the raw variance averaged over the past 252 trading days. Finally, we multiply by 100. The result is our (detrended) lagged variance series, in percentage terms. $MM_{i,t}$ is the average number of market makers across firms in each of the inside spread deciles. $D_t^{OddEighths}$ is a dummy variable which equals zero for dates prior to May 27 1994 and zero otherwise. D_t^{Jan} is a dummy for dates in the month of January, D_t^{Q3} is a dummy variable for dates in the third quarter (July through September), and D_t^{Q4} is a dummy variable for dates in the fourth quarter (October through December). The top portion of the table contains parameter estimates and HAC robust t-tests in parentheses. At the bottom the table, we present the value of R^2 for each equation, a χ^2 test for the presence of up to 10 lags of autocorrelation with 10 degrees of freedom, and a χ^2 test for the presence of up to 10 lags of ARCH with 10 degrees of freedom. We also present a Wald χ^2 test statistic, with degrees of freedom in brackets, to test whether the $Incidence_t \cdot \sigma_{i,t-1}$ coefficient estimates are jointly statistically different from each other across the inside spread series. In all cases, one, two, and three asterisks denote significance at the ten, five, and one percent level of significance respectively, based on two-sided tests. The sample period is January 4 1993 through December 29 2006.

Parameter Estimates, T-Tests, and Some Joint Tests Across Equations

	Inside Spread Decile 1	Inside Spread Decile 2	Inside Spread Decile 3	Inside Spread Decile 4	Inside Spread Decile 5	Inside Spread Decile 6	Inside Spread Decile 7	Inside Spread Decile 8	Inside Spread Decile 9	Inside Spread Decile 10	Joint χ^2 Test (P-value)
α	23.8442***	7.5392***	3.8685***	5.5233***	2.8929***	4.2778***	3.7149***	3.8220***	3.3877***	2.8639***	.
	(72.78)	(40.69)	(28.02)	(53.79)	(41.56)	(92.13)	(105.26)	(193.53)	(269.41)	(360.66)	
$\mu_{Incidence \cdot \sigma}$	-0.0383	-0.5426***	-0.4309***	-0.2761***	-0.2494***	-0.1630***	-0.0934***	-0.0332**	-0.0073	-0.0320***	437.4
	(-0.27)	(-7.17)	(-8.77)	(-6.90)	(-8.07)	(-6.71)	(-4.85)	(-2.31)	(-0.77)	(-4.60)	(0)
μ_{Volume}	-1.7536***	-2.4097***	-2.4113***	-1.7528***	-1.9472***	-1.3598***	-1.3205***	-1.0432***	-0.9162***	-0.3503***	23506.5
	(-32.25)	(-68.79)	(-86.64)	(-75.48)	(-102.45)	(-92.72)	(-98.28)	(-112.74)	(-127.85)	(-93.11)	(0)
$\mu_{Turnover}$	-0.3274***	2.3918***	3.9496***	2.3989***	2.9963***	1.8241***	1.5461***	0.7815***	0.6696***	0.2881***	10532.7
	(-6.50)	(32.86)	(57.65)	(44.59)	(68.15)	(66.57)	(65.58)	(55.09)	(60.80)	(49.01)	(0)
μ_{σ^2}	2.0205***	1.7428***	1.5081***	0.3350***	0.5089***	0.1808***	0.3249***	0.2331***	0.1489***	0.0813***	4283.7
	(34.34)	(49.92)	(57.83)	(24.32)	(31.86)	(22.35)	(32.00)	(29.63)	(25.63)	(17.51)	(0)
μ_{MM}	-1.2117***	-0.5080***	-0.3268***	-0.2519***	-0.1458***	-0.1364***	-0.0979***	-0.0693***	-0.0434***	-0.0265***	43785.1
	(-98.57)	(-91.99)	(-83.82)	(-101.38)	(-91.33)	(-122.69)	(-122.74)	(-142.13)	(-142.58)	(-160.93)	(0)
$\mu_{OddEighths}$	-7.7928***	-4.0124***	-2.9054***	-2.0996***	-1.4261***	-1.2944***	-1.0936***	-0.8056***	-0.5224***	-0.4063***	17724.0
	(-98.00)	(-105.41)	(-78.38)	(-64.18)	(-66.78)	(-85.73)	(-77.72)	(-77.19)	(-62.13)	(-65.51)	(0)
μ_{Jan}	-0.1766	0.1355	0.1599**	0.1277**	0.0631	0.1129***	0.0699**	0.0347	0.0359**	0.0138	67.5
	(-0.84)	(1.21)	(2.23)	(2.00)	(1.32)	(2.99)	(2.42)	(1.58)	(2.52)	(1.49)	(0)
μ_{Q3}	0.5145***	0.2785***	0.1300**	0.0852*	0.0458	0.0551**	0.0871***	0.0417***	0.0174*	0.0125*	80.0
	(3.30)	(3.44)	(2.44)	(1.88)	(1.38)	(2.12)	(4.05)	(2.75)	(1.75)	(1.72)	(0)
μ_{Q4}	0.4535***	0.4714***	0.2237***	0.1795***	0.1284***	0.1491***	0.1332***	0.0756***	0.0243***	0.0104**	257.8
	(4.05)	(7.89)	(5.79)	(5.59)	(5.34)	(7.90)	(8.92)	(6.80)	(3.38)	(2.07)	(0)

Diagnostic Statistics

R^2	0.654	0.714	0.790	0.771	0.819	0.847	0.873	0.900	0.922	0.873
χ^2 Test for AR(10)	67540.65***	36258.14***	29212.14***	36917.13***	26721.60***	18054.91***	23766.85***	18080.15***	4641.49***	162.07***
χ^2 Test for ARCH(10)	2969.9***	2040.9***	875.2***	1448.7***	1231.4***	355.1***	296.1***	48.9***	2.0	0.0
Economic Impact of Incidence in December	-0.037	-0.523	-0.415	-0.266	-0.24	-0.157	-0.090	-0.032	-0.007	-0.031

Joint Equation Diagnostic Statistics

Test:	χ^2 Test (P-Value)
Test for Volatility-Interacted Incidence Coefficients Equal Across All 10 Deciles	431.4 (0)

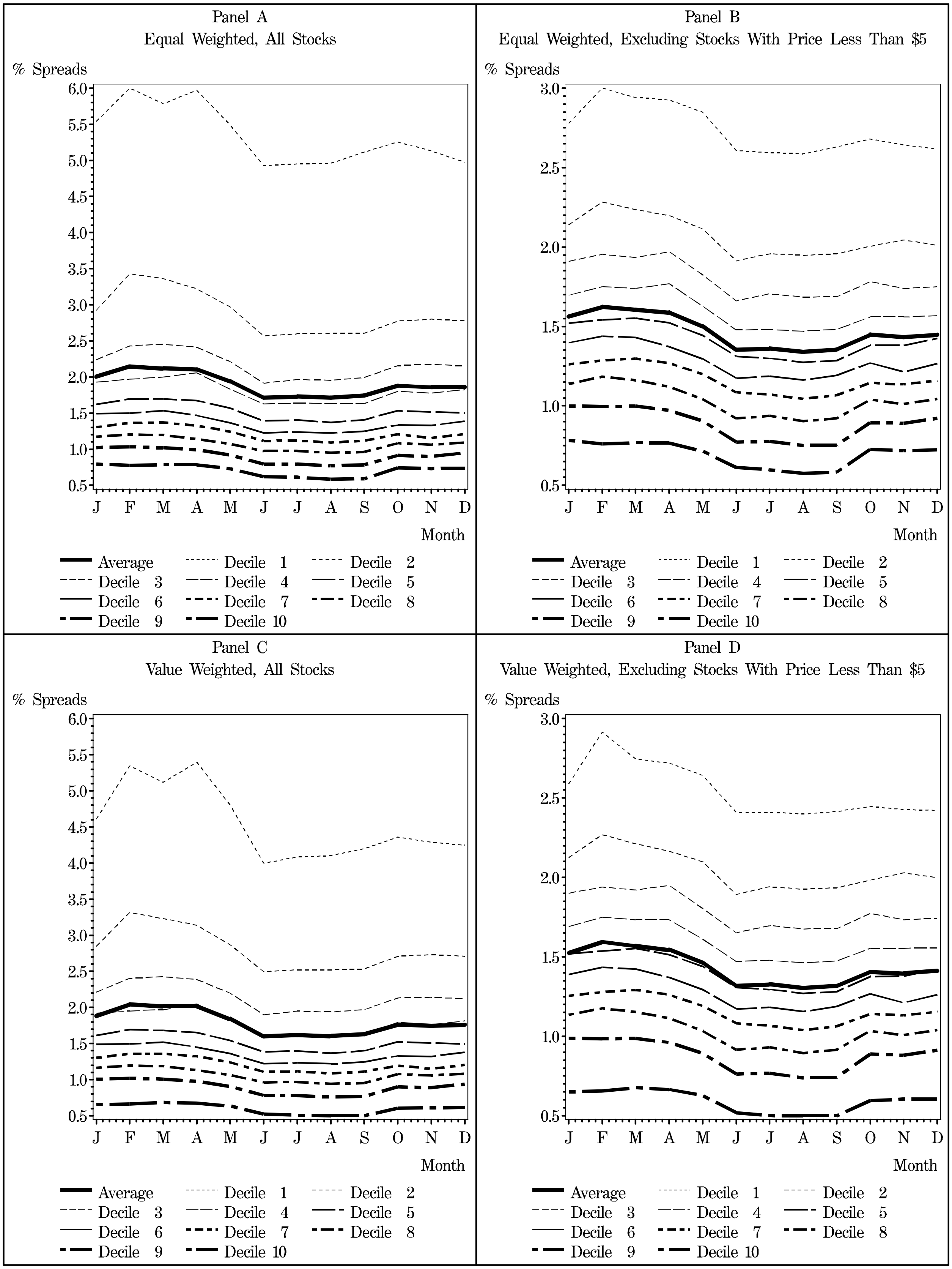

Figure 1: **Monthly Average NYSE Quoted Spreads, By Market-Cap-Sorted Deciles.** The vertical axes correspond to percentage spreads, and the horizontal axes represent months (by first letter, starting with January). Panel A presents deciles formed on all stocks, equal weighted. Panel B contains data for deciles formed on all stocks with prices greater than or equal to $5, equal weighted. Panel C presents deciles formed on all stocks, value weighted. Panel D contains data for deciles formed on all stocks with prices greater than or equal to $5, value weighted.

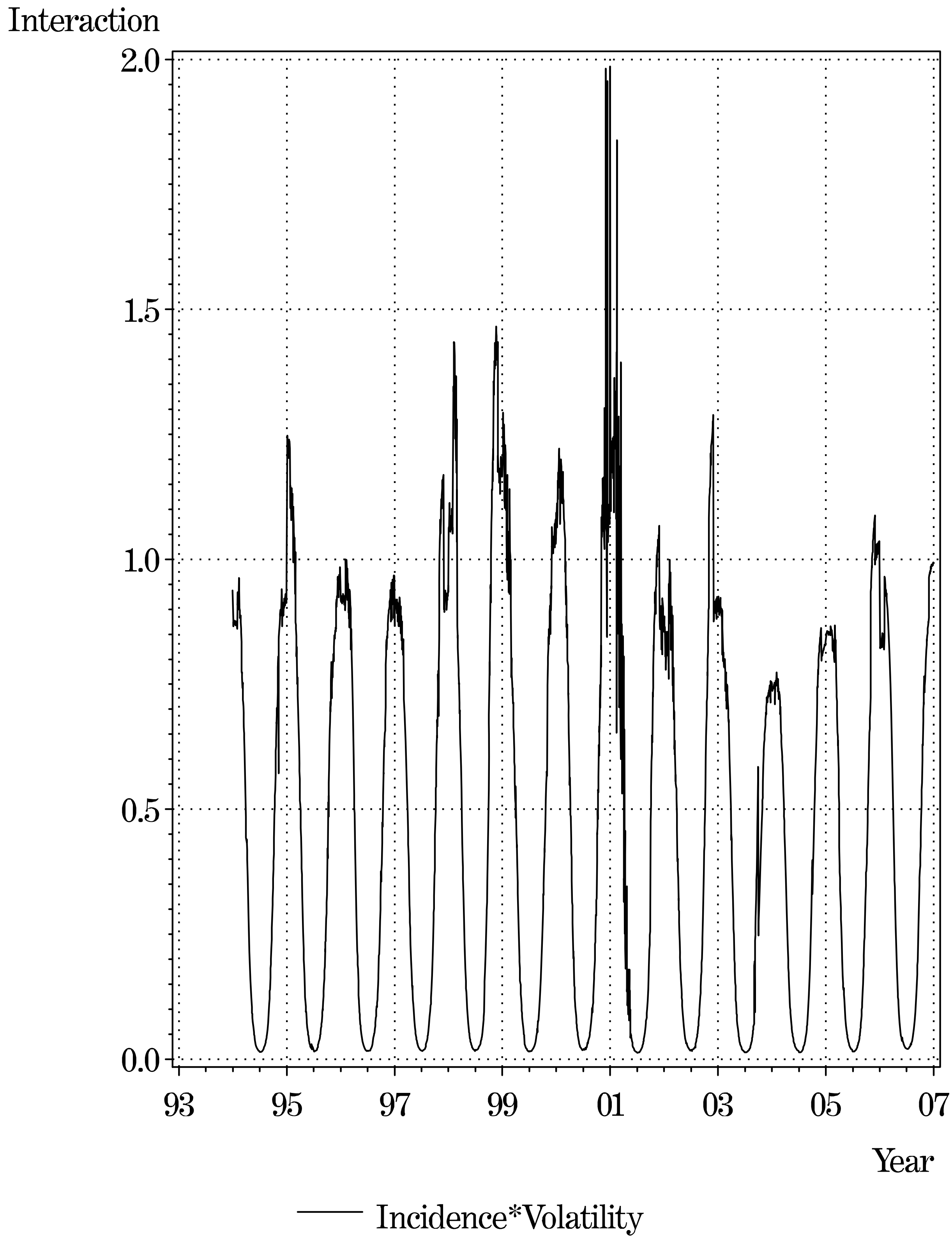

Figure 2: **Volality-Interacted Incidence Variable,** $Incidence_t \cdot \sigma_t$**.** This figure presents the daily incidence variable interacted with the lagged volatility variable for our NYSE Decile 2 during the period 1993 through 2006. The vertical axis, labeled "Interaction," depicts the value of the volatility-interacted incidence variable, while the horizontal axis indicates years by their last two digits. Note that the volatility series used for interacting with $Incidence_t$ has been normalized to have a mean of one.

Figure 3: Narrowing of the Inside Spread

With multiple heterogeneous marke makers, the inside spread narrows when a subset of the market makers experiences an increase in risk aversion due to SAD. To preserve simplicity in this diagram, we assume that the SAD-affected market makers hold a long-inventory position. though as we explain in the main body of the text, our findings do not rely on this assumption.