Does mood affect trading behavior?

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ABSTRACT

We test whether investor mood affects trading with data on all stock market transactions in Finland, utilizing variation in daylight and local weather. We find some evidence that environmental mood variables (local weather, length of day, daylight savings, and lunar phase) affect investors' direction of trade and volume. The effect magnitudes are roughly comparable to those of classical seasonals, such as the Monday effect. The statistical robustness of the mood variables is weak in most cases. Only very little of the day-to-day variation in trading is collectively explained by all mood variables and calendar effects, but lower frequency variation seems connected to vacations.

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1. Introduction

Mood – a transient state of feeling at a particular time – can influence trading decisions if it affects expectations of future fundamentals, or interacts with risk preferences (Hirshleifer, 2001; Baker and Wurgler, 2007; DellaVigna, 2009).[1] Consistent with this hypothesis, recent experimental studies find that people on good mood are more likely to make riskier choices.[2] But results of laboratory studies may not always generalize to the field, due to differences in incentives, or other factors. Furthermore, in addition to the question on the existence of a phenomenon, the question on its economic magnitude is important. The precise control available in an experimental setting may allow isolating an effect, while field evidence can provide better means of assessing its economic significance.

This paper tests for the importance of mood effects in empirical field data consisting of investors' real stock market trades in Finland. We use external, medically validated mood variables, namely hours of daylight and local whether, to measure investor mood (See e.g. Howarth and Hoffman, 1984 and Papadopoulos et al, 2005 for medical evidence). These

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[1] People on a positive mood generally assess bad outcomes as being less likely compared to people on a negative mood (Johnson and Tversky, 1983; Wright and Bower, 1992). The affect infusion model (Forgas, 1995) predicts that good mood should increase risk-taking and negative mood should depress risk-taking if the current mood primes access to memories of mood congruent outcomes from risky choices. Forgas (1998) also finds that people on good moods are more likely to resort to heuristic rather than analytical decision-making.

[2] See Yuen and Tatia (2003), Chou, Lee, and Ho (2007), Knutson et al. (2008), Kuhnen and Knutson (2011), and others.

variables have also been found to be correlated with stock market returns (Saunders, 1993; Hirshleifer and Shumway, 2003; Kamstra, Kramer, and Levi, 2003). In addition, stock returns are lower during the days immediately following a daylight savings time change (Kamstra, Kramer, and Levi, 2000), when the temperature is high (Cao and Wei, 2005), as well as during the full moon (Yuan, Zheng, and Zhu, 2006).[3] The current widespread explanation to the observed stock return effects is that they are due to the influence of mood on trading behavior. For example, Kamstra, Kramer, and Levi (2003) argue that seasonal affective disorder (SAD), a medical condition caused by lack of sunlight, leads to more risk averse behavior in the fall and winter period.

To test whether investors' tendency to buy versus sell, as well as the total volume of trade, is affected by these environmental mood variables we employ a comprehensive dataset containing all trading records of all domestic investors in Finland during 1995-2002. We have 1.1 million investors and 445 municipalities in our base data. We use the length of day, sunny weather, temperature, daylight savings, and the lunar phase as mood variables. We limit to using the

[3] A second-generation of studies confirming the earlier evidence on stock returns has emerged, see Kliger and Levy (2003), Garrett, Kamstra, and Kramer (2005), Chang et al. (2008), Dowling and Lucey (2008), and Keef and Khaled (2011). Some critical studies have also appeared. The counter arguments include data mining, same seasonal return pattern explainable by many different mood-related variables, and econometric as well as data-related problems (Goetzmann and Zhu, 2005; Jacobsen and Marquering, 2008; Kelly and Meschke, 2010). In addition, Bouman and Jacobsen (2002) and Loughran and Schultz (2004) note that a strong seasonal pattern in stock returns is not necessarily directly linked to any environmental mood *factor* despite correlation with a mood *variable*.

variables that have appeared in published studies finding stock return effects. This setting is ideal for studying the impact of environmental mood variables on trading behavior for three reasons.

First, Finland is located far up in the north and stretches 1157 kilometers (719 miles) in the north-south dimension. There is consequently a great deal of variation in the length of day in the time series as well as in the cross-section. In northern Finland above the Artic Circle (66^{o}33' N), the sun does not set around summer solstice and, correspondingly, does not rise around winter solstice. Helsinki Exchanges (part of NASDAQ-OMX Group Plc) is the second northernmost stock exchange in the world, located on 60^{o}10'N latitude, a tad south from Anchorage, Alaska (61^{o}13'N). The length of day around the summer solstice varies from 18.7 hours in southernmost Finland to 24 hours above the Artic Circle. Around the winter solstice, the length of day varies between zero in the north and 5.6 hours in the south.

Second, Finland has an area of 338,424 square kilometers, roughly the size of Germany, and contains multiple climate zones. This provides for cross-sectional variation in local weather across the 455 municipalities. For a visual representation of reasons 1) and 2), we refer to Figure 1 which shows a Mollweide map projection (maximum emphasis on having a correct projection of area at the expense of directions) of Finland, Europe and Eastern United States.

Third, sunlight deprivation associates with depression in 9% of the Finnish population, a proportion having seasonal affective disorder (SAD), fatigue (subsyndromal-SAD, or SSAD) in about 39% of the population, and as much as 85% of the population report having had some seasonal changes in mood and behavior (Grimaldi et al., 2009). The prevalence ratios in Finland are high in comparison to international figures reported in Kelly and Meschke (2010): average population prevalence of SAD is around 5% and subsyndromal-SAD around 10% globally with mixed results on the impact of latitude on SAD and SSAD prevalence (Partonen and Magnusson, 2001).

Due to these reasons we believe that, to the extent that mood changes caused by weather or length of day have an impact on investor trading decisions, such effects should show up in the trading patterns of Finnish investors, if anywhere in the world. To measure the behavioral response of investors we first classify investors into individuals, financial corporations (institutions), and other corporations. We exclude government bodies because of lack of variation in their location, and foreign investors because of missing data on their local weather conditions. We construct two behavioral outcome variables. First, we calculate a daily buy-sell –ratio for each investor group in each municipality. Note that not all investor groups can simultaneously increase (or decrease) their buy-sell –ratio because of a market level adding-up constraint. However, recall that we are excluding foreign investors and government bodies, so the investor groups that we study in this paper can all trade in the same direction. Second, as an overall measure of stock market activity, we use the number of trades generated by each investor group.

We employ two econometric approaches in assessing the impact of mood variables. First, we run a municipality-level daily panel regression, with municipality and month fixed effects, on the buy-sell –ratio. We find that the mood variables generally have the correct sign, but are not statistically significant when we cluster standard errors at the daily level.[4] The effect magnitudes

[4] The t-statistics grow by a factor of 2-4 and the effects become statistically significant if, instead of time, one clusters the standard errors along the municipality dimension.

are nevertheless comparable to classical seasonals, such as the the Monday effect.[5] For example, going from a full cloud cover to clear skies increases the buy-sell –ratio of institutions by about one percentage point (but the effect is zero for individuals). Full moon decreases the buy-sell –ratio by 1 to 3 percentage points. Classical seasonals (Monday and Friday effects, turn of the month, turn of the year) do not generally surpass these magnitudes. The exception is the last five trading days of the year for financial corporations, which causes a fall of over eight percentage points in the buy-sell –ratio.

Secondly, we run cross-sectional regression on buys versus sells for each day (or, alternatively, each week) to identify the effect of Seasonal Affective Disorder (SAD).[6] We find that the length of day has the correct sign (+) for individuals and financial corporations in weekly regression on buys versus sells, where the effect is positive in 53% of the weeks for both investor types, but not statistically significant. Some patterns we observe are inconsistent with the SAD hypothesis (i.e., that lack of exposure to daylight leads to higher risk aversion and selling stocks). For example, we find that individuals living in northern Finland tend to buy stocks during the darkest months of the year. We also utilize this cross-sectional technique for an alternative

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[5] The literature on stock market calendar effects is very large. The findings include anomalous return effects at the turn of the year (Rozeff, 1976; Reinganum, 1983), turn of the month (Ariel, 1987; Lakonishok and Smidt, 1988; Xu and McConnell, 2008), and for different days of the week (Gibbons and Hess, 1981). Thaler (1987a, b) provides a survey of the early literature. See Grimbacher, Swinkels, and Van Vliet (2010) for recent evidence combining several different effects.

[6] The effect of a slowly and deterministically moving variable such as the length of day cannot be meaningfully identified in the time series regression.

estimate of the impact of sunniness. When we limit to days with significant cross-country variation in weather, we find that the relation between sunniness and the tendency to buy stocks is positive less than 50% of the time for individuals, 51% of the time for nonfinancial corporations, and 57% of the time for financial corporations. This latter result is significant at the 5% level.

We find that there is considerable seasonal variation in both the total trading volume and the propensity to buy versus sell that seems unconnected to the length of day and sunniness. Individual investors sell relatively more stocks and trade less during the holiday season. Institutions experience a similar effect in trading volume, but their propensity to buy versus sell increases gradually from January until December. These findings are broadly consistent with the holiday hypothesis introduced by Bouman and Jacobsen (2002).

The panel regressions employing all mood variables and seasonals explain 3-4% of the variation in the buy/sell ratio for individuals and nonfinancial corporations, and 1% for financial corporations. This exceeds the R-squares of 0-2% typically reported in studies on calendar effects of stock returns such as the Monday effect (e.g., French, 1980; see Cho, Linton, Whang, 2006 for recent estimates). However, much of our models' explanatory power derives from the fixed month effects. The R-squares for trading volume are relatively high, particularly for individuals (29%), but this comes almost exclusively from the month fixed effects. The traditional seasonalities and the mood variables collectively enhance the R-squares little. Their effect in the case of individuals is less than one percentage point, and about three percentage points for financial institutions.

The remainder of this paper is organized as follows. Section 2 presents the data in more detail as well as discusses the key metrics and the econometric identification. Section 3 discusses the results and Section 4 concludes.

2. Data and methodology

A. Data sources

Our core data come from the Finnish Central Securities Depositary (FCSD), which maintains an electronic and official register of all securities transactions in Finland for virtually all companies listed in the Helsinki Exchanges (HEX, nowadays a part of NASDAQ-OMX). The data comprise daily trading account records of all Finnish investors and the sample period runs from January 1, 1995 through November 28, 2002, a period that includes both bull and bear markets. More detailed information on the data can be found in Grinblatt and Keloharju (2000).

The second key data set is from the Finnish Meteorological Institute (FMI). It supplies data on temperature (in degrees of celcius), precipitation (in mm) and sunniness (index taking values from 1 to 10)[7], all measured at noon. The weather data cover the entire FCSD data sample period, but with some gaps. There are 135 weather observation stations in Finland and we

[7] From FMI, we have a cloudiness variable between 0 and 8 indicating the number of quadrants (8 in total) entirely covered by clouds and not visible to the ground. When the clouds cannot be observed from the ground (e.g., due to heavy fog or snowstorm), the variable takes the value of 9 and in practice it is almost always completely cloudy in such cases. For ease of exposition, we reverse the scale to achieve a measure of sunniness that takes values from 1 to 10, 10 indicating a clear sky.

measure the weather condition of each municipality using the closest station.[8] We choose the closest weather station by computing the distance between the station and the center of gravity (centroid) of the municipality. Having on average 3.3 municipalities per weather station is a potential source of cross-correlation. In panel regressions we alleviate the effect of this and other possible sources by clustering the standard errors over the time unit of observation.

We use stock price data from the Helsinki Exchanges and collect daylight saving changes (as in Kamstra, Kramer, and Levi, 2000) and lunar cycles (as in Yuan, Zheng, and Zhu, 2006) from a website maintained by the University of Helsinki (http://almanakka.helsinki.fi). Descriptive statistics are reported in Table 1. We have 1.2 million investors, 445 municipalities and 13.0 million trades in our base data. In our regressions we, however, always exclude daily and weekly observations for municipalities with less than 5 trades by an investor group to reduce the number of extreme observations.

B. Measurement

We first aggregate trades on municipality and investor group level (individuals, nonfinancial, and financial corporations). We compute the buy/sell ratio based on the number of transactions (# of buys / # of buys and sells), and, alternatively, based on EUR volumes (EUR volume of buys / EUR volume of buys and sells). Then for each municipality and investor group, we consider daily (and, alternatively weekly) buy/sell ratios and detrend the variable by deducting the average annual buy/sell ratio of the investor group in each municipality. This is done to

[8] There are 445 municipalities after excluding 10 due to mergers.

exclude systematic trends such as the general positive trend in individual buying activity. In a similar fashion, we also compute excess volume by summing up the unsigned value of buys and sells. To summarize, our key dependent variables is the excess buy/sell –ratio (for each investor group) in municipality *i* on day or week *t*, detrended with corresponding figures during year *T* of observation:

$$Excessbuy/sell_{i,t} = \frac{\#of\ buys_{i,t}}{\#of\ buys_{i,t} + \#of\ sells_{i,t}} - \frac{\#of\ buys_{i,T}}{\#of\ buys_{i,T} + \#of\ sells_{i,T}} \tag{1}$$

Correspondingly, excess buy/sell volume is defined as

$$Excess\ buy/sell\ volume_{i,t} = \frac{volume\ of\ buys_{i,t}}{volume\ of\ buys_{i,t} + volume\ of\ sells_{i,t}} - \frac{volume\ of\ buys_{i,T}}{volume\ of\ buys_{i,T} + volume\ of\ sells_{i,T}} \tag{2}$$

We split investors into individuals and institutions in our descriptive analyses. In a more granular municipality level regression analyses we further split institutional investors into nonfinancial and financial corporations. Government and nonprofit organizations as well as mutual and pension funds are excluded because they have rather limited geographical variation in trades: only 8% of municipalities have 1,000 trades or more by government and nonprofit institutions during the *entire* sample period, while 3% of municipalities have at least 1,000 trades for mutual and pension funds. Foreigners trading in the Finnish stock market have the option to register their stockholdings in their own name or via a domestic financial institution using a nominee account. We cannot identify their physical location and thus the weather and length of day they are exposed to, so we exclude them from the analysis.

We calculate the length of day from sunrise to sunset (photoperiod in medical terms) with the CBM model which is most suitable for extreme latitudes (equations 1-3 in Forsythe *et al*, 1995). This method accounts for the refraction of sunlight through atmosphere. For example, the sun can be perfectly visible, although *de facto* below horizon. The correction due to refraction varies by latitude and time of year. At a maximum the effect is 75 minutes for municipalities on 66^{o}N during winter solstice.

To give a perspective on the time series and cross-sectional variation in the amount of daylight, Figure 2 shows on the map of Finland the length of day on winter and summer solstice (around December 21 and June 21) and spring and fall equinox (around on March 21 and September 21). To give a perspective on the geographic dispersion of the trades, Figure 3 plots the number of trades for both individual and institutional investors on the map of Finland. Although the trades are concentrated in metropolitan areas, we still have healthy cross sectional variation outside of the urban areas for both investor groups.

C. Identification

Of the three environmental mood variables (sunniness, lunar phase, length of day) we include the first two in panel regression analysis run at the level of municipality-days. We do not investigate the length of day with these regressions because it is a persistent variable that changes deterministically from one day to the next. The change is allmost linear within most months, although of course nonlinear throughout the whole year. We therefore investigate the effect of SAD with purely cross-sectional regressions (equations 5 and 6, discussed below) as well as in univariate analysis of seasonal trends.[9] The panel regression models are of the following form:

$$\begin{aligned} &Excess\ buy/sell_{i,t} = \alpha + \beta\ Environmental\ factors_{i,t} \\ &+ \delta\ Calendar controls_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} &Log(Excess\ \#of\ trades_{i,t}) = \alpha + \beta\ Environmental\ factors_{i,t} \\ &+ \delta\ Calendar\ controls_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where *i* indexes municipalities and *t* indexes time periods (days or weeks). The environmental factors -vector includes demeaned[10] sunniness (1 for inability to see sky, 10 for clear sky), full moon dummy (value of 1 for full moon), demeaned temperature (in Celcius), daylight saving dummy for Mondays with a daylights savings chance during the preceding weekend, and demeaned precipitation (in mm). The calendar controls vector includes separate dummies for the first five, and last five, trading days of the year, a Monday (or after holiday) dummy, Friday (or before holiday) dummy, as well as a dummy for the last 3 and 1st trading days of the month. These calendar variables are inlcuded based on studies documenting anomalous return effects at the turn of the year (Rozeff, 1976; Reinganum, 1983), turn of the month (Ariel, 1987; Lakonishok and Smidt, 1988), and for different days of the week (Gibbons and Hess, 1981).

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9 If we do nevertheless include the SAD variable in the panel regressions it gets a zero coefficient.

10 To remove pure seasonal variation, we deduct the average sunniness during the week of the observation within the 8-year sample period from the daily observation in a given municipality (i.e., an average calculated over 5 x 8 = 40 days). We apply the same procedure for temperature.

We estimate all specifications with OLS and include municipality and month fixed effects. This removes the potential effects of unobserved time invariant heterogeneity at the municipality level. The month effects remove the impact of slow-moving seasonals and market trends. We only include observations where an investor group has at least 5 trades in the municipality to reduce the skewness of the dependent variable. Since we use daily data, the dependent variables (buy-sell –ratio or log number of trades) contain important daily effects due to market level news. There is also a common national component in the environmental variables. We account for the resulting cross-sectional dependence by time-clustering the standard errors at the daily level.[11]

Our identification strategy for SAD relies on a parsimonious and strict test: cross-sectional regressions. We estimate for each time period *t* (we use weeks or days) the following models with OLS:

$$Excessbuy/sell_{i,t} = \alpha_t + \lambda_t Length\,of\;day\,in\,hours_{i,t} + \varepsilon_{i,t} \tag{5}$$

Although the effect of sunniness is already tested in the panel regressions, we estimate a similar cross-sectional model also for sunniness as an alternative test:

$$Excessbuy/sell_{i,t} = \alpha_{i,t} + \lambda_t Sunniness_{i,t} + \varepsilon_{i,t} \tag{6}$$

[11] Alternatively, cross-sectional (municipality level) clustering could be used. This results in *t*-statistics that are 2-4 times higher compared to those obtained with time clustering, and very close to regular White standard errors. This implies that the time effects are much more important in the data, in line with our intuition.

These tests identify the effects solely through their variation across the country in a given point of time. Seasonal effects do not directly influence these estimates as all time series variation has been removed. We are interested in the distribution of the coefficients λ_t. If these environmental mood variables affect trading, more than half of the coefficients should be positive. A drawback in these tests is that we can not compare the effect magnitudes to classical calendar effects, such as day-of-the-week.

Some regressors, such as sunniness and temperature, as well as the dependent variables, likely contain persistent shocks.[12] Time-clustered standard errors and the inclusion of fixed municipality effects in the baseline panel regressions may not completely eliminate a resulting downward bias in the standard errors. We therefore implement a third approach as a check of robustness: a panel data model that allows contemporaneous correlations between municipalities, and includes a common autoregressive (order one) error process in the time series dimension. Similar to the baseline panel regression, this allows utilizing both time series and cross-sectional variation, while providing an alternative method for addressing serial dependence. We include dummies for each calendar month and sample year. Including the full set of unique month fixed effects is computationally infeasible with this approach.

[12] In contrast to sunniness, lunar phase is perfectly aligned around the whole world, and so the identification comes exclusively from the time series effect. The lunar cycle is about 29.5 days and we have 103 observations of the full moon during the sample period. We use a single day dummy for the full moon, so this regressor is not persistent.

3. Results

In this section we first discuss descriptive evidence on the buy/sell ratio and trading volume. The second subsection discusses results from municipality-day -level panel regressions where we simultaneously control for all environmental variables as well as calendar effects. The third subsection discusses results from cross-sectional regressions aimed at identifying SAD.

A. Descriptive analysis

We begin by plotting the excess number of buys and sells throughout the year for an eyeball test of any obvious patterns in the data. Panel A of Figure 4 shows a clear pattern of domestic individual investors selling stocks during the summer months (May-July) and purchasing stocks during the fall months (August-October). For institutions, we observe a different pattern: a gradually increasing buy/sell ratio over the course of the year. These major patterns are not fully consistent with either the original SAD specification in Kamstra, Kramer, and Levi (2003), nor the later refinement introduced in Kamstra, Kramer, and Levi (2007).

Rather, the trading by individuals seems to be connected to vacations (Bouman and Jacobsen, 2002; Hong and Yu, 2009). Summer vacations are fairly long in Finland by international standards: full-time employees are entitled to a summer leave of about four weeks, and many have 5 to 6 weeks. July is by far the most popular month for summer holidays. The trading patterns of individual investors thus coincide quite well with the vacation season: people sell stocks before and during their summer holidays, and also early December just prior to the holiday season, and then buy stocks afterwards. This is consistent with the idea that the household sector partially finances the increased consumption during the summer vacation and the Christmas season by net sales of publicly traded stock.

Some of the minor patterns do lend support to the SAD hypothesis. KKL (2003) predicts selling pressure by SAD-investors around December, when the length of day is at its shortest. In the aggregate sample (Panel A) this is the case. However, the aggregate results are driven by individuals in southern Finland (Panel C). The behavior of individuals living in northern Finland (Panel B) with the greatest variation in daylight during the year is again inconsistent with the SAD hypothesis: these individuals buy rather than sell stocks during the darkest months.

The "onset/recovery" measure designed to account for the time-variation in SAD prevalence in KKL (2007) predicts buying by investors who do not yet suffer from SAD during August-October, and selling from investors who still suffer from SAD during February-April.[13] Consistent with this idea, there is excess buying from both individuals and institutions during August-October, and the effect is stronger for individuals located in northern Finland. During February-April, however, we observe a systematic selling pattern only for institutions.

We now turn to investigate patterns in trading volume. Figure 5 plots the weekly fraction of trading volume (number of trades in a municipality / annual number of trades), a measure that would equal 1/52 = 0.0192 throughout the year if there was no variation in trading volume. The

[13] Saarijärvi, Lauerma, Helenius and Saarilehto (1999) report that in Finland SSAD and SAD onset risk peaks in October and November with offset in March and April. These patterns are similar in the US (Young, 1997; Lam, 1998). We also obtain more recent data from the Finnish Health 2000 survey (data described in Heistaro, 2008, p. 118) and observe the onset risk to peak in October and November, with a decline during the holiday month of December and another peak at January after which onset risk starts to decline (results not reported).

result is a clear seasonal pattern: trading volume declines for both individuals and institutions significantly during the holiday months of May-August with a trough in July, the most popular summer holiday month. If investors are suffering from SAD, one would perhaps expect them to trade less during the winter months when they may fall into apathy, as pointed out by Kelly and Meschke (2010). However, this is not what we observe, neither for the full sample, nor is there any clear trend between latitude deciles.

In Figure 6 we plot the average weekly fraction of trading volume as a function of the length of day. There is a strong downward slope for both individuals (ρ = 0.66-0.67) as well as institutions (ρ = 0.45-0.46), indicating that people trade less when the day is longer. The relation is unrelated to latitude—congruent with the holiday hypothesis.

In sum, the descriptive analysis lends little support to the SAD hypothesis with the original KKL (2003) specification, but when the data is interpret with the lenses of onset/recovery measure, there is some, albeit on aggregate mixed evidence to support the SAD hypothesis. Instead, the evidence is consistent with the holiday hypothesis.

B. Panel regressions

Table 2 reports descriptive statistics for the panel sample and Table 3 shows the results for panel regressions with four specifications for both buy/sell and trading volume with three investor groups. The coefficient estimate for the sunniness variable is 0.001 for both financial and other corporations. This implies approximately a one percentage point increase in the buy/sell -ratio when going from a full cloud cover to clear skies. This effect size is similar to that of Mondays which decrease the the buy/sell -ratio by 0.6 to 2.5 percentage points, depending on investor group. The impact of sunny weather is not statistically significant, however. Furthermore, there is zero effect for individual investors, the group of investors that might be most susceptible to mood effects.

The full moon variable also has the right sign (negative) across the buy/sell specifications, with *t*-values between 1.4 and 1.6, indicating a statistically weak relation. Once again the effect magnitudes are comparable to classical seasonals: full moon decreases the buy/sell -ratio by 1.5 to 2.8 percentage points in the baseline model, thus having approximately the same impact as a weekday being a Friday.

Of the other weather variables, the results have the correct sign for precipitation (–) and daylight savings (–) in buy/sell regressions, but the sign for temperature (+) is inconsistent with the negative stock return effect found in Cao and Wei (2005). For precipitation, the coefficient is negative and significant for individuals. However, this specification uses data on only about 20% of the weather stations where precipitation is available.

The calendar control variables are all relevant for trading behavior, but their statistical significance, as well as the direction of influence, varies by investor group. Individual investors and nonfinancial corporations sell stocks on Mondays and Fridays, but only the Friday effect is statistically significant. Financial corporations sell on Mondays. Individuals strongly buy stocks in the first five trading days of the year, but the last five trading days of the year show no effects for the direction of trading. Financial corporations engage in heavy selling in the last five trading days of the year. For all investor groups trading volume increases significantly around the turn of the year, and decreases on Mondays.

C. Robustness checks for panel regression

Our dependent variables of interest (buy/sell, buy/sell volume) are persistent, especially volume. Therefore if sunny weather increases buying, its total effect might take the form of a decaying impulse. In this case controlling for the lagged dependent variable would reduce the estimated contemporaneous effect of sunniness. On the other hand, if the sun only affects such a component of trading behavior that does not carry over to the next period, then controlling for the lagged dependent variable can be appropriate to reduce noise. In unreported analysis we add the lagged dependent variable, and find that this has very little effect on the results. Estimates are generally slightly lower when controlling for lagged dependent variable which offers some support for the decaying impulse mechanism.

In unreported analysis we run all the regressions with only the mood variable of interest (sun or moon) and no calendar control variables, but including month fixed effects as usual. If the effects are statistical artifacts of a limited sample arising from some confounding seasonality (for example, suppose that during our sample period Mondays would happen to be more cloudy than other days) then the estimates for the mood variables might be stronger without controls. On the other hand, if the mood effects are genuine, then controlling for the known seasonal effects (as we do in our baseline regressions) should lead to more precise estimates for the mood variables. We find that the *t*-statistics for the mood variables indeed are slightly smaller when we drop the seasonal controls, but the differences to the baseline specification are small.

Our weather variables are measured once a day at noon. This is naturally an imperfect representation of the whole day's weather. In an attempt to capture the afternoon weather we run the regressions including a lead (tomorrow's value) of the explanatory variables. It is of course impossible that realized future whether would have a direct effect on today's trading behavior. It is, however, possible, that the forecast of tomorrow's weather would have some effect on today's behavior. Tomorrow's realized value of a weather variable is correlated with today's forecast (one would certainly hope that this is the case with weather forecasts). For example, a trader who on Thursday learns that a very nice weather is in store for Friday, might plan her work schedule so that she is able to leave early from work on the next day. This might involve working late and trading more on Thursday. Therefore, by including the lead, we capture a proxy of the current day's afternoon whether, as well as a proxy for weather related expectations. We find that in an *F*-test for the sum of the coefficients (current and lead), none of the effects are significant. When we also include the lags[14] (i.e., we have lag, current, and lead), we find the sum of the coefficients to be different from zero (at the 10% level) for the cases of precipitation with individuals as well as financial institutions, and temperature with nonfinancial corporations. This is similar to the baseline results.

As an alternative estimation method we employ a panel data model with an AR(1) error structure in the time dimension (results not reported). We do not include a full set of month effects in this specification to ease the computational burden, but rather use a dummy for each calendar month and year. The results show that, compared to the baseline panel regressions, the *t*-statistic for the full moon dummy is now somewhat higher (at 2.03) for individuals, and similar

[14] The evidence in the psychology literature of a possible lagged effect of whether on mood is mixed. Persinger (1975) finds a lagged effect up to two days, but Sanders and Brizzolara (1982) do not find any such effects using a larger data sample.

to the baseline for other investor groups. As with the baseline results, the impact of sunniness is not statistically significant. There is a negative and significant Friday effect for all investor groups, as well as negative and significant Monday effect for both types of corporations, but not for individuals. The patterns around the turn of the year are similar to the baseline results: financial corporations sell during the last five trading days of the year, and individual investors buy during the first five trading days of the year. However, the estimated standard errors are larger compared to the baseline regressions, leading to marginal statistical significance (*t*-statistic of 1.91 and 1.87, respectively). Consistent with "Sell in May and go away" (see Bouman and Jacobsen, 2002), the buy-sell –ratios are 2 to 6 percentage points lower in the month of May, and these effects are statistically significant for individuals as well as financial institutions. Individuals also live up to the other part of the rule, and "buy back in St. Leaguer day" (in September) or by the time of Halloween (in October). The estimates are about 3.5 for both of these month dummies and highly statistically significant.

D. Cross-sectional regressions

In this section we move on to a scrutinizing test of the SAD hypothesis (excess buy/sell is related to length of day) by way of purely cross-sectional identification. We do this because identifying a slow-moving length of day –effect is problematic in a daily panel regression. We also utilize this technique for a further test of the weather hypothesis which was nevertheless already tested using the panel regressions.

Table 4 reports descriptive statistics and Table 5 shows the estimation results. In a daily specification, the coefficient for regressing individual excess buy/sell volume on the length of day is positive for 53% (*t*-value of 2.01) of the fall weeks. For the number of transactions, 51% (*t*-value of 0.69) of the fall weeks have positive coefficient. The weekly results for the length of day and both daily and weekly results for sunniness are not statistically significant. The coefficient for nonfinancial corporation daily volume regression on the length of day has negative sign and is unexplainable by the SAD hypothesis.

We also entertain the possibility that we do not detect the impact of sunny weather because all observations are pooled into one regression and the cross-sectional variation of weather can be small in some days or weeks. Table 6 reports daily results for sunniness when we only consider the top quintile of observations with most between municipality variation in sunniness. For individuals, the coefficient for sunniness is positive in less than 50% of regressions. For nonfinancial corporations the coefficient is positive in 51-52% of the time, which is not statistically significantly higher than 50%. For financial corporations, the results show positive coefficients in 54-57% of the cases, and this latter figure is statistically significant at the 5% level.

One of the strongest conclusions in the medical literature on SAD is that women are more affected than men, although men are more likely to experience other major depressive disorders (e.g., Partonen and Lönnqvist, 1998; Saarijärvi *et al* 1999). Odds ratios up to 16:1 have been reported in extreme cases for female vs. male prevalence of SAD (e.g., Hellekson, 1989). Motivated by these findings we report in Table 7 cross-sectional results separately for men and women. In line with the prediction from the medical literature, the results are stronger for women with 60% of positive coefficients (vs. 57% for men) for a weekly buy/sell volume regression, but the difference is not statistically significant. Conclusions are similar from the daily data: there is no significant gender effect, although in both number of transactions as well as volume regressions the coefficient is larger for women than for men.

Taken together, the results from cross-sectional analysis with results reported in Tables 5 through 7 show mixed results regarding the impact of sunniness and the length of day.

4. Conclusion

This paper started by asserting that Finland provides a great setting for testing whether mood has an impact on investors' trading behavior. The results show that sunniness has a positive effect on the demand for stocks, and full moon has a negative effect, consistent with the studies that associate these variables with stock returns. Also precipitation and daylight savings effects have the predicted negative signs, but temperature does not. However, the effects are in most cases statistically insignificant, or not robust to alternative specifications. We find little evidence of Seasonal Affective Disorder affecting trading behavior as measured by the length of day. The clearest patterns in the data seem to be connected to holiday seasons, as well as the turn of the year. Investors trade less during vacations overall, and trade in a direction consistent with financing vacation related consumption.

Alternative to focusing on statistical significance, one can compare the environmental mood variables with classical seasonals (such as the Monday effect), on which there is a huge literature. The effect magnitudes are by and large the same. In a sense of Bayesian statistical inference, a reasonable prior might be that the classical seasonal effects are real. Hence, also the environmental mood effects could turn out statistically significant when being evaluated jointly across multiple samples in future studies. Based on our findings we nevertheless conclude that from the standpoint of overall economic significance, neither day-to-day mood changes unconnected to any fundamentals nor the classical calendar effects seem to exert a major influence on investors' trading decisions.

The variables that we study are thought to be instruments of investor sentiment. Yet we hesitate to draw any conclusions between the findings of this study and the broader role of sentiment in financial markets. Different mechanisms are likely at play when sentiment is affected by more salient events, builds over a longer term, interacts with fundamentals (as with the cross-section of firm characteristics and stock returns), or has a social element. For example, Edmans, Garcia and Norli (2007) find a negative stock market reaction following soccer World Cup losses. Kaplanski and Levy (2010) show that aviation disasters lead to large immediate negative market reactions that reverse in the course of the following weeks. These papers argue that the market effects are brought by sudden changes in investor mood. Such discrete events may have stronger effects on trading behavior than the more mundane changes in the environment that we study.[15] The hypothesized mechanism is still the same: exogenous events impact investors' mood, leading to changes in optimism or risk aversion, or both, which in turn affect trading decisions. An analysis along the lines of this paper, where we have limited to environmental mood variables, applied to these discrete events would be interesting as well.

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[15] Strictly speaking, daylight savings time switch, or sudden changes in weather do represent discrete changes. But contrary to major sports events or disasters, such effects are still normally very mundane.

To our knowledge, this is the first paper to study the effect of mood on trading behavior with comprehensive data. However, we may not be aware of unpublished work finding weak results between mood and trading behavior, or no results between potential other environmental factors and asset prices, given that many well crafted papers with no significant results may end up unpublished, and thus never reach a wider audience.

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Table 1

Descriptive statistics on the investor data

This table presents descriptive statistics on the panel data where the unit of observation is municipality with daily data from January 1, 1995 through November 28, 2002. In subsequent descriptive analyses, trades by institutional investors are aggregated into one group. In regression analyses, only individual investors, nonfinancial corporations and financial corporations are considered.

Panel A: Number of investors and trades in the base sample

Number of domestic investors in the sample	1,178,333	
Number of individual investors	1,119,406	
Number of institutional investors	58,927	
Number of nonfinancial corporations	45,102	
Number of financial corporations	753	
Number of mutual and pension funds	77	
Number of government and nonprofit institutions	12,995	
Number of trades by domestic investors in the sample		
by individual investors	7.2	million
by institutional investors		
by nonfinancial corporations	2.34	million
by financial corporations	3.49	million
by mutual funds	0.17	million
by government and nonprofit institutions	0.16	million
Value of trades by domestic investors in the sample		
by individual investors	52.7	billion
by institutional investors		
by nonfinancial corporations	128.42	billion
by financial corporations	300.37	billion
by mutual funds	18.35	billion
by government and nonprofit institutions	8.04	billion

Panel B: Municipality statistics

Number of municipalities in Finland in 1995	455
Number of municipalities removed from sample due to merger	10
Number of municipalities with never 5 or more trades per day	1
Number of municipalities in the sample	444

Table 2

Descriptive statistics on the municipality-level as used in panel regression

The sample includes all trades by domestic investors (individuals, nonfinancial corporations and financial corporations) during the sample period of 1995-2002. There is one observation for each municipality-day, and 444 municipalities in total. To enter the sample, the municipality must have at least 5 trades by the investor group in the given day. Panel A presents statistics for the dependent variables. Panle B presents the statistics for independent variables using the valid observations from individual investors. Other investor groups have slightly different values due to missing some municipalities. Buy/sell is defined as # of buys / (# of buys and sells). *Sunniness* takes value of 1 for days when sky cannot be observed and 10 for clear sky. *Full moon* is a dummy for full moon days. *Last 5 trading days of year*, *First 5 five trading days of the year, Monday or after holiday*, *Friday or before holiday*, and *Last 3 and 1st trading of* month are seflf-explanatory calendar dummy variables. *Daylight saving* dummy takes value of 1 if during the preceding weekend (daylight savings changes always happen on Sundays). *Precipitation* is the amount of rain in mm.

	Min	Mean	Median	Max	St.dev.	Skewness	Kurtosis	N
Panel A. Dependent variables								
Individuals								
Buy/sell	0.00	0.51	0.50	1.00	0.26	-0.04	2.47	200,597
# of trades	5.00	35.78	11.00	4569.00	136.70	12.79	228.90	200,597
Nonfinancial corporations								
Buy/sell	0.00	0.51	0.50	1.00	0.27	0.01	2.44	44,488
# of trades	5.00	52.58	10.00	3017.00	187.80	6.57	53.23	44,488
Financial corporations								
Buy/sell	0.00	0.50	0.50	1.00	0.30	0.01	2.39	6,866
# of trades	5.00	508.70	13.00	7669.00	1067.49	2.46	8.50	6,866
Panel A: Independent variables								
Sunniness (index)	1.00	4.23	3.00	10.00	2.55	0.86	2.32	200,597
Full moon dummy	0.00	0.04	0.00	1.00	0.19	4.89	24.91	200,597
Last 5 trading days of year	0.00	0.02	0.00	1.00	0.15	6.55	43.85	200,597
First 5 trading days of year	0.00	0.03	0.00	1.00	0.16	6.03	37.33	200,597
After holiday dummy	0.00	0.21	0.00	1.00	0.41	1.41	2.98	200,597
Before holiday dummy	0.00	0.23	0.00	1.00	0.42	1.31	2.72	200,597
Turn of the month dummy	0.00	0.17	0.00	1.00	0.38	1.75	4.06	200,597
Temperature, celcius	-44.40	6.16	5.20	31.80	10.41	-0.12	2.63	200,597
Daylight saving dummy	0.00	0.01	0.00	1.00	0.09	11.32	129.20	200,597
Precipitation, mm	0.00	1.65	0.40	44.90	3.07	3.78	25.18	39,386

Table 3

Results from panel regressions

The depended variable is excess buy/sell (buy/sell – annual average buy/sell) or demeaned zero skewness log number of trades (*Log*(# of trades) – annual average *Log*(# of trades)). The base sample includes all trades by domestic investors in all Finnish stocks during the sample period of 1995-2002. There is one observation for each municipality/day combination and the sample is divided to domestic individuals, nonfinancial corporations and financial corporations. To enter the sample, the municipality must have at least 5 trades by the investor group in the given day and be in the sample of 444 municipalities (10 municipalities excluded due to merger, other missing municipalities are due to less than 5 trades). *Sunniness* takes value of 1 for days when sky cannot be observed and 10 for clear sky, demeanded by using the average annual amount of sunlight in the municipality. *Full moon* is a dummy for full moon days. *Last 5 trading days of year First 5 five trading days of the year, Monday or after holiday*, *Friday or before holiday*, and *Last 3 and 1st trading of* month (Lakonishok and Smidt, 1988) are self-explanatory calendar dummy variables. *Daylight saving* dummy takes value of 1 if during the preceding weekend (daylight savings always happen on Sunday) there was a daylight savings change. *Precipitation* is the amount of rain in mm, demeaned. Each specification also includes a constant and they are estimated with OLS, results estimated with weighted least squares are available from the authors upon request. Asterisks mark statistical significance at conventional levels (*** for 1%, ** for 5%, and * for 10%).

Panel A: Individuals

	Excess buy/sell				Excess zero skewness log # of trades			
Sunniness (demeanded)	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.003
	0.02	0.05	0.02	1.00	0.97	0.90	0.85	1.18
Full moon	-0.017	-0.018	-0.018	-0.012	-0.017	-0.016	-0.017	-0.048
	1.60	1.61	1.63	0.85	0.58	0.53	0.56	1.13
Last 5 trading days of year	0.002	0.003	0.003	-0.008	0.081	0.077	0.077	0.072
	0.17	0.22	0.22	0.53	2.47**	2.39**	2.40**	1.66*
First 5 trading days of year	0.037	0.036	0.036	0.030	0.159	0.162	0.161	0.151
	2.48**	2.45**	2.44**	1.55	5.37**	5.39***	5.35***	3.66***
Monday or after holiday	-0.006	-0.006	-0.006	-0.004	-0.028	-0.028	-0.025	-0.037
	1.39	1.38	1.22	0.59	2.63***	2.66**	2.32*	2.41**
Friday or before holiday	-0.018	-0.018	-0.018	-0.014	0.026	0.026	0.026	0.022
	3.31***	3.31***	3.31***	2.04**	2.31*	2.29**	2.28**	1.43
Last 3 and 1st trading day of month	-0.004	-0.004	-0.004	-0.006	-0.016	-0.016	-0.016	-0.034
	0.81	0.8	0.79	0.85	1.43	1.46	1.45	2.12**
Temperature (demeaned)		0.000	0.000	0.001		-0.002	-0.002	-0.001
		0.71	0.71	1.41		1.70	1.69*	0.60
Daylight saving			-0.018	-0.042			-0.094	-0.062
			0.98	1.82*			2.34**	0.99
Precipitation (demeaned)				-0.002				0.001
				3.01**				0.42
Constant	0.160	0.161	0.161	0.170	-4.327	-4.329	-4.329	-5.245
	3.88***	3.89***	3.89***	24.78***	58.64***	57.90***	57.97***	61.87***
# of observations	200,597	200,597	200,597	39,386	200,597	200,597	200,597	39,386
Number of municipalities	444	444	444	144	444	444	444	144
Adjusted R-squared	0.03	0.03	0.03	0.04	0.29	0.29	0.29	0.28

Panel B: Nonfinancial corporations								
	Excess buy/sell				Excess zero skewness log # of trades			
Sunniness (demeanded)	0.001	0.001	0.001	-0.001	-0.001	-0.001	-0.001	-0.004
	1.44	1.33	1.35	0.71	0.82	0.72	0.71	1.21
Full moon	-0.015	-0.016	-0.016	-0.005	-0.001	0.001	0.000	0.010
	1.59	1.64	1.66	0.30	0.03	0.02	0.01	0.22
Last 5 trading days of year	0.010	0.012	0.012	0.010	0.079	0.075	0.075	0.038
	0.75	0.92	0.92	0.48	2.88***	2.75***	2.75***	1.06
First 5 trading days of year	0.005	0.003	0.003	0.006	0.103	0.107	0.106	0.093
	0.30	0.18	0.17	0.30	3.69***	3.76***	3.75***	2.39**
Monday or after holiday	-0.006	-0.006	-0.006	-0.010	-0.065	-0.065	-0.064	-0.083
	1.47	1.45	1.30	1.46	6.68***	6.71***	6.51***	5.29***
Friday or before holiday	-0.016	-0.016	-0.016	-0.014	-0.002	-0.002	-0.002	-0.012
	3.67***	3.65***	3.65***	2.13**	0.20	0.23	0.23	0.74
Last 3 and 1st trading day of month	-0.011	-0.011	-0.011	-0.009	-0.015	-0.016	-0.016	-0.035
	2.36**	2.33**	2.33*	1.38	1.56	1.58	1.58	1.96**
Temperature (demeaned)		0.001	0.001	0.002		-0.002	-0.002	0.001
		2.18*	2.18**	2.87***		1.87	1.87	0.79
Daylight saving			-0.017	-0.039			-0.024	-0.070
			0.83	2.60**			0.62	1.45
Precipitation (demeaned)				-0.001				-0.003
				0.97				1.82*
Constant	-0.016	-0.015	-0.015	0.043	-4.163	-4.165	-4.165	-5.177
	0.34	0.32	0.32	4.54***	46.16***	46.18***	46.17***	68.70***
# of observations	44,488	44,488	44,488	11,173	44,488	44,488	44,488	11,173
Number of municipalities	354	354	354	107	354	354	354	107
Adjusted R-squared	0.01	0.01	0.01	0.01	0.18	0.18	0.18	0.15

Panel C: Financial corporations								
	Excess buy/sell				Excess zero skewness log # of trades			
Sunniness (demeanded)	0.001	0.001	0.001	-0.001	-0.003	-0.003	-0.003	0.003
	0.57	0.51	0.49	0.35	1.23	1.17	1.15	0.49
Full moon	-0.028	-0.028	-0.027	-0.023	0.029	0.029	0.029	0.055
	1.43	1.45	1.43	0.62	0.81	0.82	0.81	0.83
Last 5 trading days of year	-0.087	-0.086	-0.086	-0.104	-0.029	-0.030	-0.031	0.037
	3.33***	3.29***	3.28***	2.61***	0.50	0.53	0.54	0.47
First 5 trading days of year	-0.008	-0.009	-0.008	0.002	0.142	0.144	0.143	0.135
	0.3	0.34	0.31	0.06	2.78***	2.79***	2.78***	1.38
Monday or after holiday	-0.025	-0.025	-0.027	-0.028	-0.111	-0.111	-0.109	-0.103
	3.01***	3.00***	3.21***	1.90*	6.58***	6.61***	6.34***	3.72***
Friday or before holiday	0.002	0.002	0.002	-0.018	0.008	0.008	0.008	0.007
	0.21	0.23	0.24	1.27	0.53	0.51	0.51	0.28
Last 3 and 1st trading day of month	-0.005	-0.005	-0.005	-0.001	-0.017	-0.017	-0.017	0.014
	0.62	0.62	0.63	0.06	0.99	0.99	0.99	0.47
Temperature (demeaned)		0.001	0.001	-0.001		-0.001	-0.001	0.001
		0.68	0.68	0.34		0.66	0.66	0.35
Daylight saving			0.063	-0.004			-0.086	0.037
			1.75	0.04			1.31	0.41
Precipitation (demeaned)				-0.003				0.003
				1.91*				0.82
Constant	-0.002	-0.001	-0.001	-0.082	-4.437	-4.439	-4.439	-5.129
	0.06	0.03	0.02	5.85***	21.96***	21.92***	21.93***	183.4***
# of observations	6,866	6,866	6,866	2,008	6,866	6,866	6,866	2,008
Number of municipalities	174	174	174	52	174	174	174	52
Adjusted R-squared	0.01	0.01	0.01	0.01	0.09	0.09	0.09	0.09

Table 4

Descriptive statistics for cross-sectional analysis

This table presents descriptive statistics on the pooled panel data where the unit of observation is municipality with daily and weekly data from January 1, 1995 through November 28, 2002. The data is used in the cross-sectional regressions with results reported in Table 5. Variables are also described in Table 5.

	Min	Mean	Median	Max	St.dev.	Skewness	Kurtosis	N
Individuals								
Buy/sell	0	0.51	0.50	1.00	0.25	-0.04	2.49	228,596
Buy/sell volume	0	0.50	0.50	1.00	0.29	0.01	2.14	228,596
Sunniness (index)	1	4.22	3.00	10.00	2.54	0.86	2.34	196,597
Length of the day (hours)	0	11.79	11.43	24.00	4.98	0.10	1.80	228,596
Nonfinancial corporations								
Buy/sell	0	0.51	0.50	1.00	0.27	0.00	2.42	50,408
Buy/sell volume	0	0.51	0.50	1.00	0.29	-0.01	2.25	50,408
Sunniness (index)	1	4.32	3.00	10.00	2.54	0.79	2.22	43,142
Length of the day (hours)	0	11.78	11.44	24.00	4.86	0.11	1.80	50,408
Financial corporations								
Buy/sell	0	0.50	0.49	1.00	0.30	0.01	2.33	7,071
Buy/sell volume	0	0.51	0.50	1.00	0.31	0.00	2.32	7,071
Sunniness (index)	1	4.35	3.00	10.00	2.54	0.76	2.19	6,859
Length of the day (hours)	0	11.95	11.63	20.75	4.51	0.07	1.68	7,071

Table 5

Results from cross-sectional regressions for SAD and Sunniness

This table presents results for binomial z-test for the impact of amount *Sunniness* (from 1 to 10) and *Length of day* (the number of hours between sunset and sunrise) on investor group. The unit of observation is municipality and day/week. In Panel A, dependent variable detrended buy/sell (# of buys by investor group / (# of buys and sells by investor group in municipality) – average buy/sell ratio for the investor group in the municipality in the year of observation) is computed weekly for each three investor groups in each municipality and regressed on *Sunniness* or *Length of day* and a constant. Buy/sell volume is defined as buy/sell, but by using actual EUR volumes instead of # of transactions. z-test statistic is computed with binomial test as (% of positive coefficients when regressing buy/sell ratio on *Sunniness* or *Length of day* for each municipality) / (0.5*0.5/Number of observations in the regression)$^{0.5}$. The sample period runs from January 1, 1995 through November 28, 2002. *, **, and *** denote significance (2-tailed) at 10%, 5%, and 1% levels, respectively.

Panel A: Weekly regression

Independent variable	Results	Individual Buy/sell	Individual Buy/sell volume	Nonfin. corp. Buy/sell	Nonfin. corp. Buy/sell volume	Fin. corp. Buy/sell	Fin. corp. Buy/sell volume
Sunniness	# of regressions during weeks 1-53	403	403	403	403	403	403
	% of positive coefficients	49%	49%	54%	50%	49%	51%
	z-test	*-0.35*	*-0.25*	*1.44*	*-0.05*	*-0.35*	*0.55*
	total # of municipality/week observations	94,605	94,605	25,756	25,756	4,031	4,031
Length of day	# of regressions during weeks 1-13 and 39-53	203	203	203	203	203	203
	% of positive coefficients	53%	51%	45%	48%	53%	44%
	z-test	*0.77*	*0.35*	*-1.47*	*-0.49*	*0.91*	*-1.61*
	total # of municipality/week observations	104,882	104,882	29,106	29,106	4,319	4,319

Panel B: Daily regression

Independent variable	Results	Individual Buy/sell	Individual Buy/sell volume	Nonfin. corp. Buy/sell	Nonfin. corp. Buy/sell volume	Fin. corp. Buy/sell	Fin. corp. Buy/sell volume
Sunniness	# of regressions during weeks 1-53	1918	1918	1918	1918	1412	1412
	% of positive coefficients	48%	49%	52%	52%	52%	51%
	z-test	*-1.46*	*-1.19*	*1.83**	*1.42*	*1.28*	*0.96*

	total # of municipality/day observations	200,597	200,597	44,488	44,488	6,866	6,866
Length of day	# of regressions during weeks 1-13 and 39-53	919	919	919	919	880	880
	% of positive coefficients	51%	53%	51%	46%	49%	49%
	z-test	*0.69*	*2.01***	*0.43*	*-2.54***	*-0.34*	*-0.74*
	total # of municipality/day observations	233,246	233,246	52,134	52,134	7,079	7,079

Table 6

Results from cross-sectional regressions with top-quintile Sunniness variation

This table presents results for binomial *z*-test for the impact of amount *Sunniness* (from 1 to 10) for top quintile of observation days with most cross-sectional variation in the actual amount of sunlight. The unit of observation is municipality and day. The specification is identical to Table 5. The sample period runs from January 1, 1995 through November 28, 2002. *, **, and *** denote significance (2-tailed) at 10%, 5%, and 1% levels, respectively.

Ind. variable	Results	Daily regression					
		Individual		Nonfin. corp.		Fin. corp.	
		Buy/sell	Buy/sell volume	Buy/sell	Buy/sell volume	Buy/sell	Buy/sell volume
Sunniness	# of regressions during weeks 1-53	361	361	361	361	315	315
	Percentage of positive	47%	46%	51%	52%	57%	54%
	z-test	*-1.11*	*-1.63*	*0.47*	*0.58*	*2.31***	*1.30*
	total # of municipality/day observations	44,624	44,624	9,858	9,858	1,436	1,436

Table 7

Results from cross-sectional regressions for SAD by gender

This table presents results for binomial *z*-test for the impact of the length of day on trades by individual investors by gender. The unit of observation is municipality and day/week. The specification is identical to Table 5. The sample period runs from January 1, 1995 through November 28, 2002. *, ** and *** denote significance (2-tailed) at 10%, 5% and 1% levels.

Ind. variable	Results	Panel A: Weekly regression			
		Males		Females	
		Buy/sell	Buy/sell volume	Buy/sell	Buy/sell volume
Length of day	Number of regressions during weeks 1-13 and 39-53	203	203	203	203
	Percentage of positive	51%	57%	50%	60%
	z-test	*0.21*	*1.90**	*0.07*	*2.88****
	total # of municipality/week observations	51,638	51,638	16,068	16,068

Ind. variable	Results	Panel B: Daily regression			
		Males		Females	
		Buy/sell	Buy/sell volume	Buy/sell	Buy/sell volume
Length of day	Number of regressions during weeks 1-13 and 39-53	918	918	918	918
	Percentage of positive	52%	55%	52%	55%
	z-test	*0.92*	*2.97****	*1.52*	*3.10****
	total # of municipality/day observations	205,355	205,355	65,208	65,208

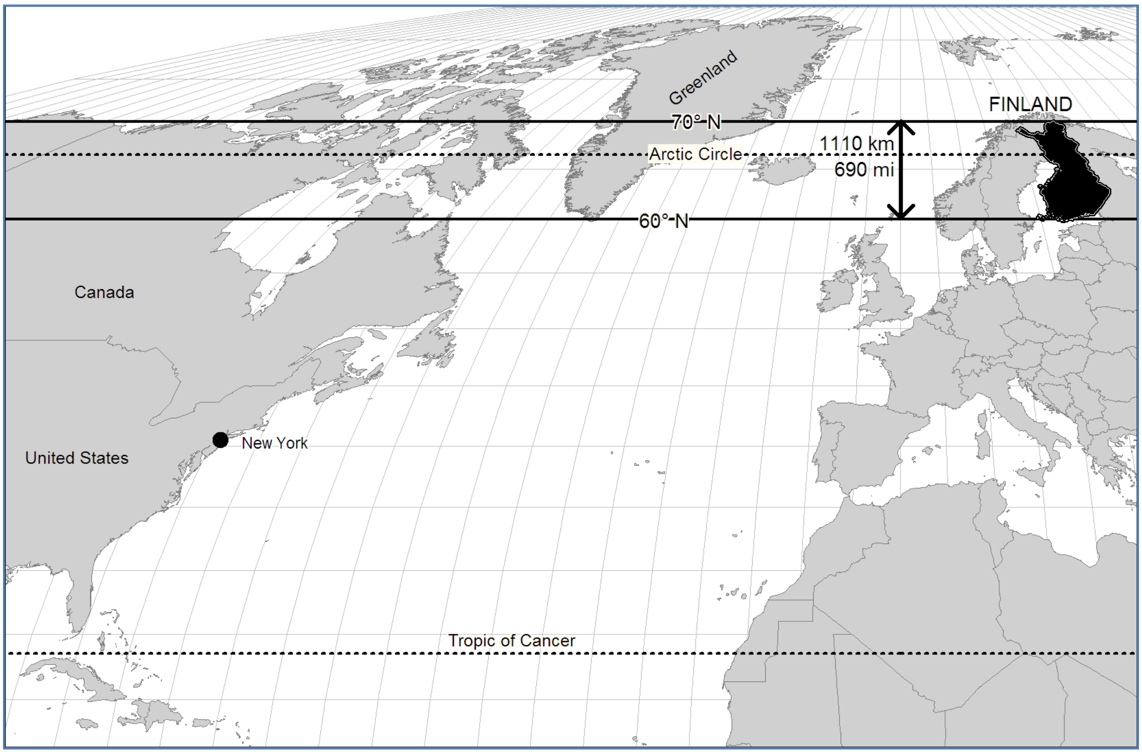


Figure 1. Location of Finland. The figure above depicts the Mollweide projection (priority on accurate representation of area rather than direction) of Finland, Europe and eastern United States.

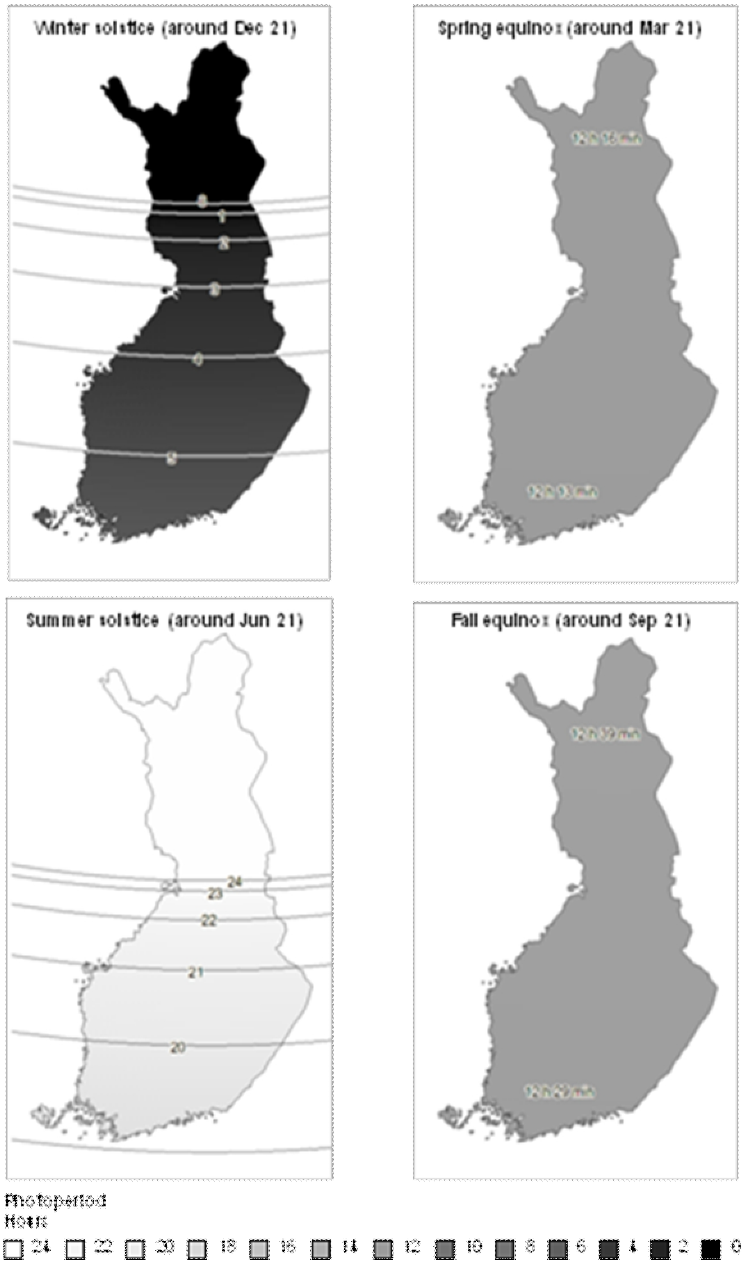


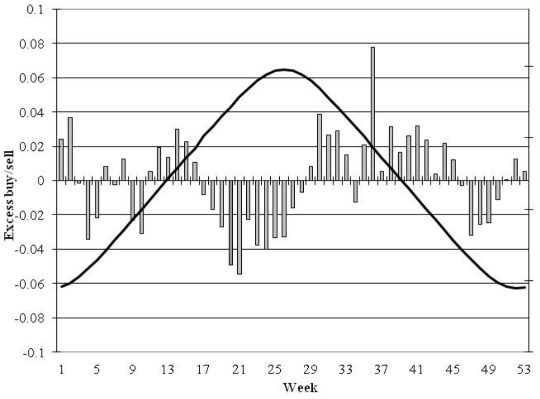
Figure 2. Length of day (number of hours between sunset and sunrise) during winter solstice, spring equinox, summer solstice and fall equinox. The four maps show the length of day in hours with isocurves marking the line for exact hours during the time.

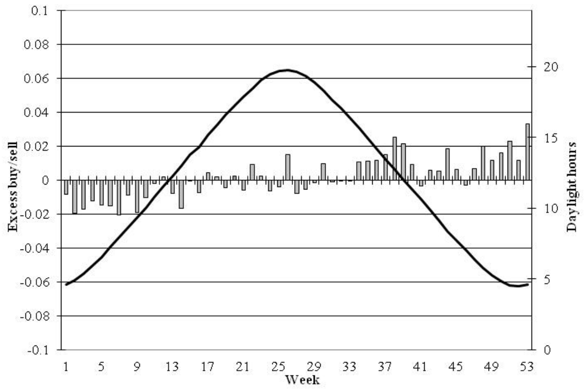
Individuals **Institutions**

Figure 3. Geographic representation for number of trades in the sample. The left hand side graph plots the number of trades for domestic individual investors with one dot representing 1000 trades over the sample period from January 1, 1995 through November 28, 2002. The right-hand side figure plots the number of trades for domestic institutional investors with all institutional investors pooled into one sample.

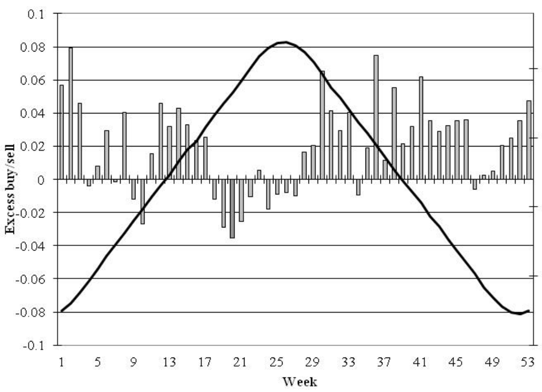
Individuals **Institutions**

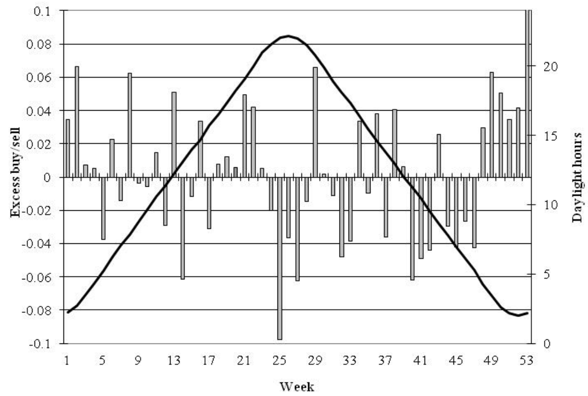
Panel A: Whole Finland (59.9-69.7 degrees northern latitude)



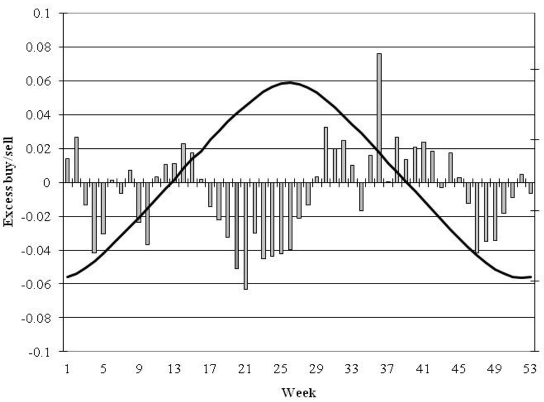


Panel B: Northern Finland (more than 64 degrees latitude)





Panel C: Southern Finland (less than 62 degrees northern latitude)



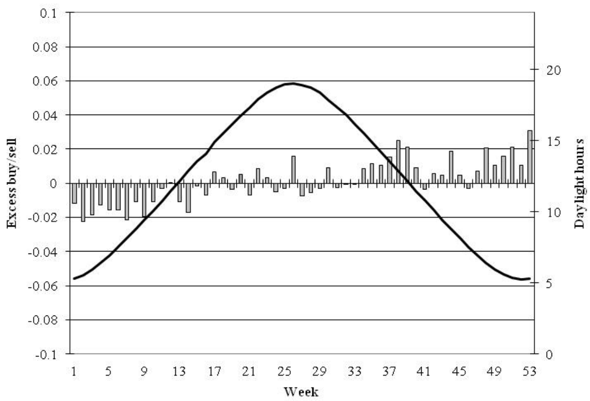
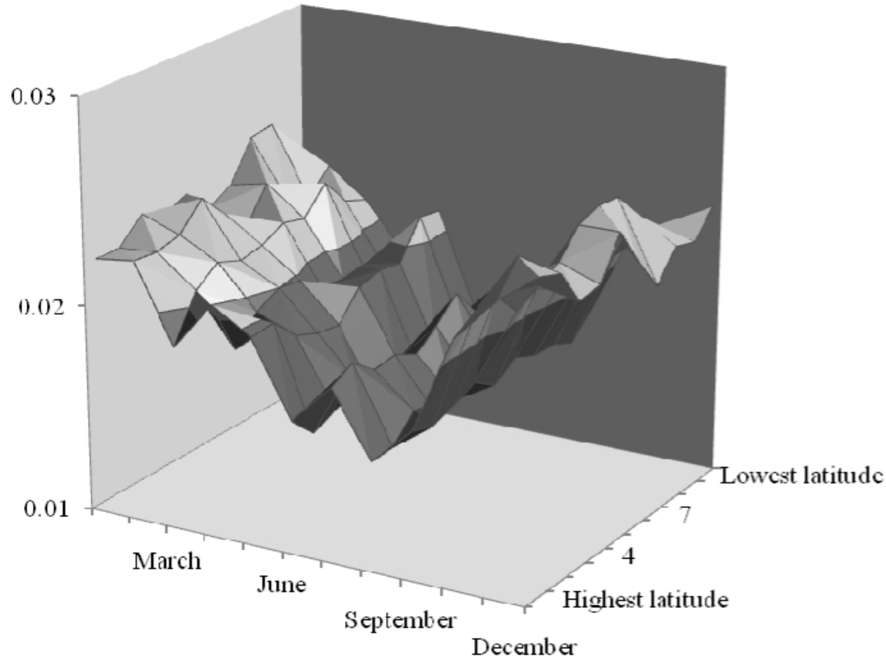


Figure 4. Daylight and excess buy/sell ratio. The excess buy/sell ratio is defined as weekly # of buys / (weekly # of buys + weekly # of sells) – annual # of buys / (annual # of buys + annual # of sells). The data include all transactions by domestic investors in Finland. The number of trades for calculating each graph are 8,405,166 (individuals in the whole country; also including individuals with unknown domicile); 6,262,902 (individuals in southern Finland); 666,987 (individuals in northern Finland); 6,539,397 (institutions in the whole country); 6,200,096 (institutions in southern Finland) and 80,496 (institutions in northern Finland).

Individuals



Institutions

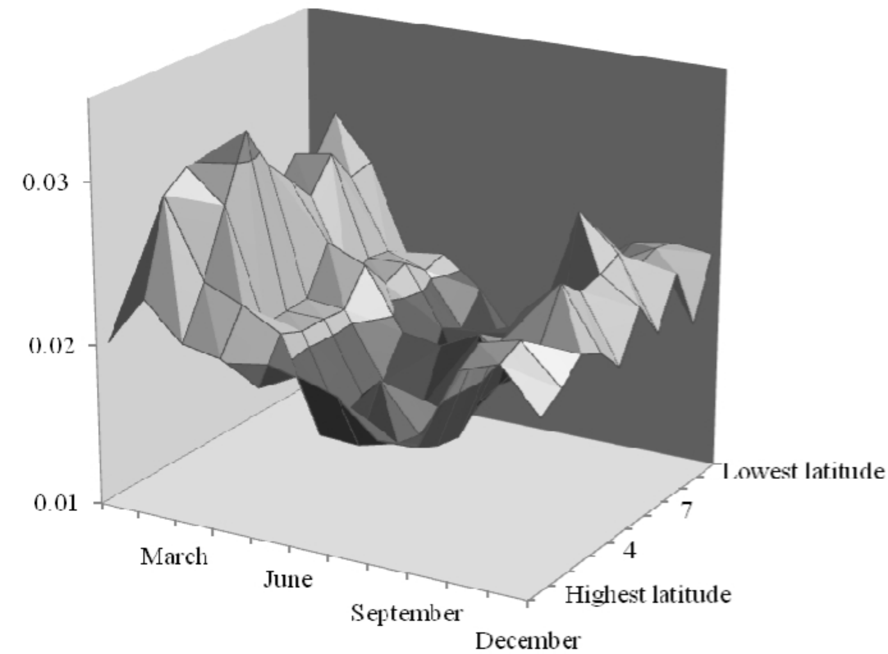
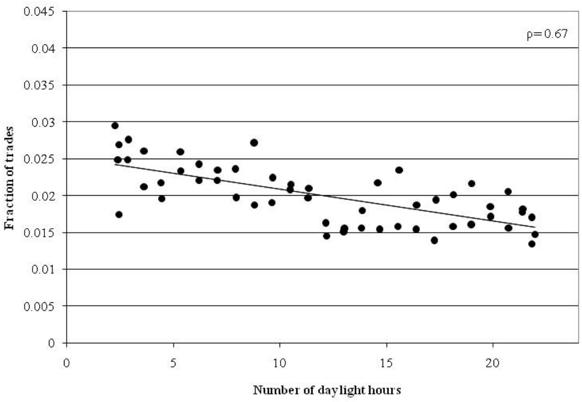


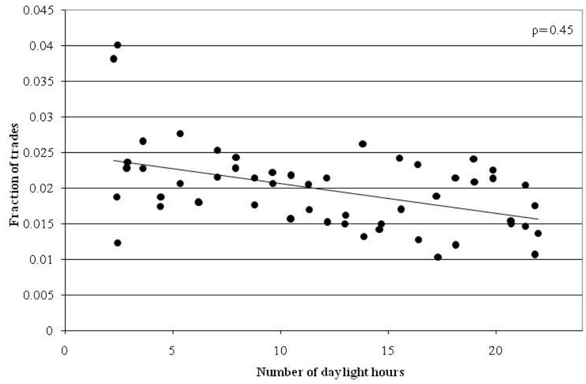
Figure 5. Excess volume ratio (weekly number of trades / annual number of trades) by month and latitude, based on all transactions by domestic investors in Finland. The number of observations is 170,872 for households and 12,257 for institutions.

Panel A: Northern Finland (more than 64 degrees latitude)

Individuals

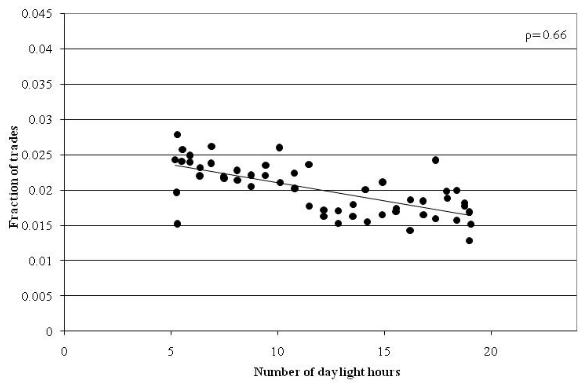


Institutions



Panel B: Southern Finland (less than 62 degrees latitude)

Individuals



Institutions

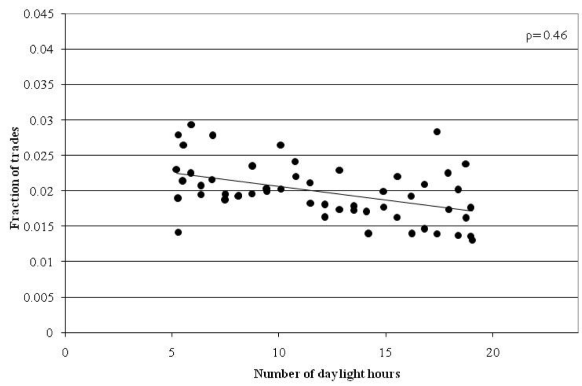


Figure 6. Daylight and volume. The plotted fraction volume is defined as weekly number of trades/annual number of trades. The analysis includes all transactions by domestic investors in Finland. The scatterplot observations represent the average weekly volume fractions of annual volume. The averages are calculated from daily observations by averaging over each week and municipality. The number of observations for the four figures are 76,958 (individuals, southern Finland); 20,740 (individuals, northern Finland); 45,950 (institutions, southern Finland); and 7,570 (institutions, northern Finland).