Does mood affect trading behavior? *

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The assumption that mood affects investors' behavior in the field is gaining acceptance due to experimental studies and papers linking stock returns with environmental variables, such as weather and length of day. To identify mood effects this paper utilizes account level stock trading data from all investors in Finland, a country with significant variation in weather and length of day. While some weather-related mood variables and calendar effects are individually significant, little of the day-to-day variation in trading is collectively explained by all such factors. In contrast, we find strong seasonal lower frequency patterns that seem 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] In this paper we provide the first comprehensive evaluation of the hypothesis that mood impacts investor behavior in the field, using account level transaction data from all domestic investors in Finland. Our main instruments for measuring mood are hours of daylight and local weather, both medically validated mood proxies (e.g., Keller et al., 2005; Papadopoulos et al., 2005). To the extent that people are more optimistic about stocks or have higher risk tolerance when they are on a better mood, we would expect them to be more inclined to buy rather than sell stocks when the day is longer or when there is more sunshine. Hours of daylight and amount of sunshine have also been found to correlate with stock market returns at the country level.[2]

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

[2] See Saunders (1993) and Hirshleifer and Shumway (2003) for sunshine, and Kamstra, Kramer, and Levi (2003) for hours of daylight.

However, unlike the prior studies on stock returns, we examine the direct link between mood and investors' trading actions. This distinction is important as a statistical correlation between an environmental mood variable and stock returns can arise in multiple ways.[3]

Our main data come from the official registry of stock holdings in Finland. Our sample period is 1995-2002. In addition to providing account level transaction data, 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 1,157 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. At the winter solstice on December 21, the length of day in Finland varies between zero above the Arctic Circle in the north (66°33'N) and 5.6 hours in the southernmost tip. At the summer solstice on June 21, the length of day varies from 18.7 hours in the south to 24 hours in the north.

Second, Finland has an area of 338,424 square kilometers, roughly the size of Germany, and comprises multiple climate zones. This provides cross-sectional variation in local weather across

[3] There is an active debate concerning the implications of the country level studies correlating environmental mood variables with stock returns. Several studies confirm the earlier evidence on stock returns and extend findings to other asset classes (Kliger and Levy, 2003; Garrett, Kamstra, and Kramer, 2005; Kamstra, Kramer, and Levi, 2007; Chang et al., 2008; Dowling and Lucey, 2008; De Silva, Pownall, and Wolk, 2012). However, 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, 2009; Kelly and Meschke, 2010; Novy-Marx, 2014). 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.

the 455 municipalities in the country. For a visual representation of reasons one and two, we refer to Figure 1 for a map of Finland, Europe, and the Eastern United States. Third, seasonal affective disorder (SAD) due to sunlight deprivation is somewhat more prevalent in Finland by international standards (Partonen and Magnusson, 2001; Kelly and Meschke, 2010). Of the total population, 85% report at least some seasonal changes in mood and behavior (Grimaldi et al., 2009).

Due to the above reasons, we believe that, to the extent that mood changes caused by weather or length of day impact trading decisions, such effects should show up in Finland, if anywhere in the world. Additionally, we use *temperature* (Cao and Wei, 2005) and *precipitation* (Saunders, 1993), as these variables have also been linked to mood in psychology and medical literature, found to be correlated with stock returns, and have both cross-sectional and time-series variation, ideal for our panel data setup.

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 location and local weather. We then construct a behavioral outcome variable: daily *buy ratio* (# of buys / (# of buys + # of sells)) for each investor group in each municipality. We focus on the buy ratio as the mood hypothesis makes a clear prediction regarding the direction of trade: people on positive mood are more likely to buy than sell conditional on making a trade. Not all investor groups can simultaneously increase (or decrease) their buy ratio because of a market level adding-up constraint. However, recall that we are excluding foreign investors (constituting approximately 45% of trading volume), so the domestic investor groups that we study could all trade in the same direction.

We expect different investor groups to exhibit heterogeneous responses to mood factors. Individuals are thought to be more influenced by mood than corporations, which typically involve many individuals and experts in their decision-making process (Elsbach and Barr, 1999; Shapira and Venezia, 2001). Financial corporations, the most savvy investor group we study, should show the smallest response to mood factors, or even a response opposite to individuals, due to providing liquidity to mood-induced individuals. The other corporation category we study includes non-financial corporations as well as investment vehicles of wealthy individuals. We expect these investors to be between individuals and financial corporations in sophistication, and hence also in their susceptibility to mood effects.

We employ two econometric approaches in assessing the impact of mood variables on trading. First, we run a municipality-level daily panel regression on the *buy ratio*. We include municipality and month fixed effects, and cluster standard errors at the daily level. We find that the weather-related mood variables, *sunniness*, *temperature*, and *precipitation*, generally have the correct sign, and the effect magnitudes are comparable to classical seasonals, such as the Monday effect. For example, going from a full cloud cover to clear skies increases the *buy ratio* of financial institutions by 1.7 percentage points. The effect is 0.9 percentage points for nonfinancial corporations, but, contrary to the mood hypothesis, smallest (0.2 percentage points) for individual investors. However, the effects of *sunniness* and *temperature* are generally statistically insignificant whereas the weekend effect, for example, is significant for all investor groups (whether it is the Monday or Friday side of it varies by investor group). Strong effects are also associated with the *last five trading days of the year* for financial institutions and the *first five trading days of the year* for individual investors. Of the weather variables, *precipitation* is most consistent: it is negative for all investor groups, and statistically significant for individuals (1%) and financial institutions (5%).

Precipitation is correlated with humidity,[4] which is known to have a negative effect on mood, and is the single strongest effect among eight weather-related mood variables investigated by Howarth and Hoffman (1984). Nonetheless, the predictive power from all mood variables combined is extremely small by any measure.

While we believe our conservative-leaning baseline econometric specification is appropriate given the data, as discussed in more detail below, we also entertain several alternative models that can be considered more lenient (reported in the Internet Appendix). None of these specifications, however, lead to materially different conclusions.

Our second econometric approach is used primarily for identifying the effect of SAD. We run a cross-sectional regression on detrended excess buys versus sells for each day (or, alternatively, each week). This detrending removes all time variation individually for each municipality and constitutes a tough but precise test.[5] The SAD hypothesis, as described in Kamstra, Kramer, and Levi (2003) and Garrett, Kamstra, and Kramer (2005), says that lack of exposure to daylight leads to higher risk aversion and selling stocks. Thus, at a given point in time, investors in areas having shorter days should be more prone to selling stocks than investors living in areas with longer days. We find that the *length of day* has the correct sign (+) in regressions on the *excess buy ratio* for individual investors and nonfinancial corporations. However, it is statistically significant only in the case of daily regressions for individuals where 53% of the coefficients are positive. Furthermore, some patterns in the data are even opposite to the SAD hypothesis. For example, we

[4] Unfortunately our weather station data does not include a direct measure of humidity.

[5] We describe the exact detrending procedure for excess buys versus sells (labeled as *excess buy ratio*) in the cross-sectional regression in Section 3.3.

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 estimate of the impact of sunniness. When we limit our analysis to days with significant cross-country variation in weather, we find that the relation between *sunniness* and the tendency to buy stocks is positive 53% of the time for individuals, 51% of the time for nonfinancial corporations, and 52% of the time for financial corporations. None of those results are statistically significant, however.

We could of course also employ other measures on trading behavior, such as propensity to buy riskier stocks, day trading activity, disposition effect, local bias, and profitability of trades for detailed analysis. We do not address these trading outcomes in detail in this paper for two reasons. First, the hypothesis on mood affecting direction of trade has been well developed in the literature (e.g., Kamstra, Kramer, and Levi, 2003) while clear ex ante hypotheses involving other more precise measures of trading activity are currently underdeveloped. Several authors (e.g., Hirshleifer and Shumway, 2003; Kamstra, Kramer, and Levi, 2003; Bassi, Colacito, and Fulghieri, 2013) empirically agree on a general level that better mood promotes risk-taking behavior, but finer-print theory how mood would impact the propensity to take systematic and idiosyncratic risk, skewness preference or other measures is lacking. Second, any findings rejecting the null hypothesis would be subject to a valid concern for data mining. We retain the focus of this paper almost exclusively on the direction of trade, but report results analogous to the buy ratio for trading volume and subsamples in the Internet Appendix.

The two major contributions of this paper are as follows. First, it brings field evidence to bear on the question of whether mood changes affect investment behavior.[6] Experimental studies find that people in a good mood are more likely to make riskier choices (Yuen and Lee, 2003; Chou, Lee, and Ho, 2007; Knutson et al. 2008; Kuhnen and Knutson, 2011). Bassi, Colacito, and Fulghieri (2013) document that people are more risk tolerant in a lottery choice task when the experiment is conducted on a sunny day. However, the results of laboratory studies may not always generalize to the field, due to differences in incentives, or other factors (Harrison, List, and Towe, 2007). Furthermore, in addition to the question of the existence of a phenomenon, the question of its economic magnitude is important. The precise control available in an experimental setting may allow isolating an effect, while field evidence can provide a better means of assessing its economic significance. Our overall conclusion from the standpoint of economic significance, as evidenced by their contribution to model adjusted R-squared, is that day-to-day mood changes induced by weather and unconnected to any fundamentals do not seem to exert a major influence on investors' trading decisions.

[6] The only related prior field study so far is Goetzmann and Zhu (2005), who analyze sunniness and the trading behavior of brokerage account investors in five U.S. cities. Similar to us, they too fail to find a consistent effect for sunniness. However, their paper has done little to change the prevailing consensus that sunlight affects investors, an interpretation made based on the stock return studies of Saunders (1993) and Hirshleifer and Shumway (2003). This is likely due to a perceived lack of power in their tests that utilize only five geographical locations (two of these locations — New York and Philadelphia — often have the same weather). The principal differences between our study and theirs are that we analyze a set of seasonal and weather-related factors (not just sunniness), include all market participants (not just retail clients at one brokerage), we utilize a setting that allows meaningful variation for purposes of identification, and we develop new methods for this task.

Second, we jointly analyze all seasonalities and weather-related variables linked to the stock market. While there is a vast literature documenting calendar effects in stock returns,[7] much less is known about the corresponding effects on trading behavior. An exception is Grinblatt and Keloharju (2004), who study trading behavior around the turn of the year. In addition to turn of the year effects, we analyze other calendar variables based on documented stock return anomalies at the turn of the month (Ariel, 1987; Lakonishok and Smidt, 1988; McConnell and Xu, 2008), for days of the week (French, 1980; Gibbons and Hess, 1981), and other holidays and vacations (Bouman and Jacobsen, 2002). We find strong evidence of individuals buying in the beginning of the year, and individuals as well as nonfinancial corporations selling on Fridays and before holidays. Domestic financial institutions sell on Mondays and after holidays, and foreign investors buy. Other classical calendar effects do not show up consistently in investors' trading behavior. On a lower frequency, there is considerable seasonal variation throughout the year in total trading volume as well as buy ratios that seems unconnected to the length of day and sunniness. Individual investors sell relatively more stocks before, and trade less during holiday seasons. The monthly trading patterns of individuals are also consistent with the "Sell in May and go away" effect and the holiday hypothesis in Bouman and Jacobsen (2002). Institutions experience a similar effect in trading volume, but their propensity to buy versus sell increases gradually from January to December. All in all, the seasonal patterns are consistent with individual investors selling stocks prior to vacation seasons and shorter breaks. This could be related to financing vacation consumption, reducing the need to monitor and stress about investments, or simply a need for

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[7] Thaler (1987a, 1987b) provides a survey of the early literature. See Swinkels and Van Vliet (2012) for more recent evidence.

mental closure. These potential explanations are not mutually exclusive, but some measure of the mental closure aspect is needed to explain all patterns: individuals also sell ahead of the weekend, over which monitoring is not needed as the markets are closed, and the cash is only received next week due to a settlement lag.

We proceed by presenting the data and key measures in more detail in Section 2. In Section 3, we discuss econometric identification. In Section 4, we describe the main results, and in Section 5 we discuss additional results and robustness checks. Finally, we conclude in Section 6.

2. Data and measurement

2.1. 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 on 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. All trades we identify are based on active decisions: automated savings plans did not exist in the Finnish stock market during the sample period. More detailed information on a subset of the data can be found in Grinblatt and Keloharju (2000).

The second key dataset is from the Finnish Meteorological Institute (FMI), which supplies data on *temperature* (in Celsius), *precipitation* (in mm), and *sunniness* (index taking values from 1 to

10),[8] 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 measure the weather condition of each municipality using the closest station.[9] We chose 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.

To finalize our data, we use stock price data from the HEX. Descriptive statistics are reported in Table 1. There are 1.2 million investors, 455 municipalities, and 13 million trades in our base data. In our panel regressions and cross-sectional analysis, we always exclude daily and weekly observations for municipalities with fewer than five trades by an investor group to reduce the number of extreme observations.[10]

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[8] From the FMI, we have a cloudiness variable between 0 and 8 indicating the number of quadrants (8 in all) entirely covered by clouds and not visible from the ground. When the clouds cannot be observed from the ground due to thick fog or a heavy snowstorm, for example, 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, with 10 indicating a clear sky.

[9] There are 444 municipalities after excluding 11 due to mergers and lack of data during the sample period.

[10] A reader familiar with the literature regressing stock returns on environmental variables could ask whether these relations are also present in the Finnish stock return data. Using data for 1970-1998, we estimate the models of Kamstra, Kramer, and Levi (2003, 2007) and establish results for SAD and sunshine (Saunders, 1993) consistent with earlier literature. For *precipitation* and *temperature*, we are unable to establish a robust statistical relation. Similar to other developed markets, Finland experienced a period of high volatility with a stock market upswing and crash during

Finally, we also contacted all Finnish municipalities by letter during June-September 2011 to enquire about their primary school (1st to 9th grade) holiday periods during the sample period. Although the broad holiday seasons are congruent across the country (around Christmas and from early June until mid-August), municipalities set the exact schedules. Variation occurs as municipalities schedule summer recess and spring, fall, and Christmas breaks slightly differently and sometimes give an extra day off if a national holiday falls on Thursday or Tuesday. We obtain school holiday data on 236 (53%) of the municipalities. Missing data on the rest of the municipalities is in most cases due to their failure to centrally maintain these records from 9 to 16 years back.

2.2. Measurement

We first aggregate trades at the municipality and investor group level (individuals, nonfinancial, and financial corporations). Consistent with earlier literature (Grinblatt and Keloharju, 2000), we compute the buy ratio based on the number of transactions (# of buys/(# of buys + # of sells)). Then, for each municipality and investor group, we consider daily (and, alternatively, weekly) buy ratios. For each investor group in municipality *i* on day or week *t*:

$$Buy\ ratio_{i,t} = \frac{\#of\ buys_{i,t}}{\#of\ buys_{i,t} + \#of\ sells_{i,t}}. \tag{1}$$

1999-2001. Using a sample for 1970-2002 or 1995-2002 (our trading data period) produces coefficients similar to those from the 1970-1998 period, but generally not statistically significant as higher return volatility in 1999-2002 adds more noise. These stock return results are reported in Appendix 1.

We split investors into individuals and institutions in our descriptive analyses. In 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 can identify neither their physical location nor 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 Center for Biosystems Modeling (CBM) model, which is the most suitable for extreme latitudes [equations 1-3 in Forsythe et al. (1995)]. This method accounts for the elliptical orbit of the earth and refraction of sunlight through atmosphere. For example, the sun can be perfectly visible, although it is actually below the horizon. Refraction has not been accounted for in earlier literature on daylight and stock returns where observations come from less extreme latitudes. In our data, especially in the northern parts of the country, refraction can be substantial: at a maximum, the refraction effect is 75 minutes for municipalities at 66°N latitude during the 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 the winter and summer solstice (around

December 21 and June 21) and spring and fall equinox (around March 21 and September 21).[11] To give a perspective on the geographical dispersion of the trades, Figure 3 shows the number of trades for both individual and institutional investors on the map of Finland. Although the trades are concentrated in metropolitan areas, there is a good amount of cross-sectional variation outside urban areas for both investor groups.

3. Identification strategy

Our overall identification strategy is based on identifying the effect of mood solely from the residual variation after accounting for geographic and time fixed effects. This ensures that we are not confusing seasonality or geographic differences in trading behavior with mood effects. Environmental mood variables, such as weather, are heavily correlated with seasons and geography. Instead of simply regressing trading activity on environmental mood variables and potentially confusing seasonality and geographic differences in trading activity with a confounding mood variable, we first take out any systematic seasonal and geographic trends and then ask whether the residual variation is attributable to mood. Our approach is also being adopted in a paper by Schmittmann et al. (2015) developed subsequently to our paper.

3.1. Is this strategy too conservative?

To avoid throwing out the baby with the bathwater, we also experiment with alternative and more lenient econometric models. We believe these alternative models are less well specified than our

[11] Using CBM instead of a more simplified model also explains why the length of the day is not exactly 12 hours around the equinoxes in Figure 2.

baseline model, but they can be thought of as robustness analysis on the issue of whether we are in some sense controlling for too much. The results from these alternative more lenient models and specifications are discussed in Section 5.2. (using raw buy ratio instead of detrended buy ratio), Section 5.6. (leaving out calendar control variables), and Section 5.7. (cross-sectional instead of time clustering), but these results are typically noisier and they do not generally lead to conclusions that are different from the baseline results.

3.2. *Identification and model selection*

Our empirical part consists of two sets of analyses. The first one uses daily panel regressions run at the municipality level. We include *sunniness*, *precipitation*, and *temperature* in these regressions. We do not investigate the length of day with this method because it is a persistent variable that changes deterministically from one day to the next. The change is almost linear within most months, although of course nonlinear throughout the whole year. We therefore investigate the effect of SAD on the buy ratio with purely cross-sectional regressions (discussed later) as well as in univariate analysis of seasonal trends.[12] The panel regression models, estimated with OLS, are of the following form:

$$\begin{aligned} Y_{i,t} &= \alpha + \beta\, Environmental\ factors_{i,t} + \delta\, Calendar\ controls_{i,t} \\ &+ \varphi\ Municipality\ fixed\ effect + \gamma\, Month\ fixed\ effect + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where the dependent variable $Y_{i,t}$ is the *buy ratio*, *i* indexes municipalities, and *t* indexes time periods (days or weeks). The environmental factors vector includes *sunniness* (1 for inability to

[12] If we do, nevertheless, include the SAD variable in the panel regressions, it gets a zero coefficient. See Section 5.8.

see sky, 10 for clear sky), demeaned *temperature* (in Celsius),[13] 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 three and first trading days of the month. These calendar variables are included based on studies documenting anomalous return effects at the turn of the year (Rozeff and Kinney, 1976; Reinganum, 1983), turn of the month (Ariel, 1987; Lakonishok and Smidt, 1988), and for different days of the week (Gibbons and Hess, 1981).

Following our identification strategy, all specifications include municipality (up to 444 municipalities) and each month (95 months) 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 five trades in the municipality to reduce the skewness of the dependent variable. Since we use daily data, the *buy ratio* contains important daily effects due to market level

[13] Consistent with our identification strategy described in Section 2.3. and earlier literature regressing stock returns on mood variables (e.g., Hirshleifer and Shumway, 2003), we remove pure seasonal variation in *temperature* and *precipitation*. We do this by deducting the average temperature 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 precipitation. The rationale for this is the significant seasonal variation: temperature, for example, varies from -44 degrees Celsius (-47 degrees Fahrenheit) to +32 degrees Celsius (+90 degrees Fahrenheit). Without demeaning, these highly seasonal weather variables would mainly capture the time of the year [see also Jacobsen and Marquering (2008) for a discussion). This demeaning of the temperature and precipitation variables is different from the detrending of the dependent variable for the cross-sectional analysis.

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.

The second set of analyses that we run are geared toward identifying the effect of SAD via cross-sectional variation in the length of day. We do this using a two-step approach. First, we identify the municipality-specific level and time trend and remove them from the data. Specifically, we estimate the following *excess buy ratio* model separately with weekly and daily data for each municipality *i*:

$$Excess\,buy\ ratio_{i,t} = \alpha_i + \beta_i^1 T + \beta_i^2 T^2 + \varepsilon_{i,t}, \tag{3}$$

where T is the time index variable with β_1 capturing possible linear and β_2 nonlinear time trends in the data. This detrending procedure is an application of Frisch and Waugh's (1933) theorem and does not introduce a look ahead bias: it is analogous to including municipality fixed effects and municipality-specific time trend in a regression where the buy ratio is not detrended. We then use the residuals from equation (3) as the dependent variable. These residuals (denoted *excess buy ratio*) now exclude the municipality-specific constant (α_i) as well as the linear (β^1) and squared (β^2) time trend unique to each municipality. In the second step, we use OLS to estimate for each time period *t* (weeks or days) the following models:

$$Excess\,buy\,ratio_{i,t} = \alpha_t + \lambda_t Length\,of\ day\,in\,hours_{i,t} + \varepsilon_{i,t}. \tag{4}$$

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

$$Excess\,buy\,ratio_{i,t} = \alpha_{i,t} + \lambda_t Sunniness_{i,t} + \varepsilon_{i,t}. \tag{5}$$

Equations 4 and 5 identify the mood effects solely through their variation across the country at a given point in time. Seasonal or municipality-specific effects do not directly influence these estimates as all time series and municipality-level variation have been removed. We are interested in the distribution of the λ_t coefficients. If these environmental mood variables affect trading, more than half of the coefficients should be positive. We also experiment with specification using raw buy ratio without detrending, but using this approach does not alter our main conclusions. Results for the raw buy ratio are given in Internet Appendix 2.

3.3. Why not investor-level identification?

Our identifying variation is not at investor level. We therefore use group average identification (Angrist and Pischke, 2008, p. 313) to avoid the Moulton problem of understating standard errors when the identification is at a more granular level than the source of identifying variation. Schmittmann et al. (2015) find statistically significant results for mood effects among a sample of active German retail investors, although their results could be attributable to incorrect clustering at the investor level (e.g., Angrist and Pischke, 2008, pp. 308-310).

4. Results

In this section, we first discuss descriptive evidence of seasonal patterns on the *buy ratio*. This is relevant, particularly for assessing the lower frequency implications of the SAD hypothesis. In the second subsection, we discuss results from daily panel regressions with observations at the municipality level where we simultaneously control for all environmental variables as well as calendar effects. In the third subsection, we discuss results from cross-sectional regressions aimed at identifying SAD.

4.1. Seasonal patterns

We begin by plotting the abnormal *buy ratio*[14] 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 spring and summer months (May-July) and purchasing stocks during the end of summer and fall (August-October). For institutions, we observe a different pattern: a gradually increasing buy 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, on aggregate, the trading by individuals seems to be connected to vacations at weekly intervals (Bouman and Jacobsen, 2002; Hong and Yu, 2009; Jacobs and Weber, 2012). 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 five to six 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 end-of-year holiday season, and then buy stocks after these periods. This is consistent with the idea that the household sector partially finances the increased consumption during the summer vacation period and the end-of-year season by net sales of publicly traded stock.

[14] For ease of visual inspection, we only remove the annual trend in the buy ratio in Figure 4, rather than removing the overall time trend described in Equation 3. If the number of buys and sells are equal in a given week, Figure 4 would render into a flat pattern on the x-axis.

Some of the minor patterns in Figure 4 do lend support to the SAD hypothesis. The Kamstra, Kramer, and Levi (2003) length of the day measure is predictive of the selling pressure by SAD investors around December, when the length of day is the shortest. This is the case in the aggregate sample (Panel A). 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. In addition, the fall dummy original specification of Kamstra, Kramer, and Levi (2003) would also be expected to increase selling pressure in the fall season (September 21 to December 20), but this pattern is not present in the data either.

The "onset/recovery" measure, designed to account for the time variation in SAD prevalence in Kamstra, Kramer, and Levi (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.[15] 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.

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[15] Saarijärvi et al. (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 U.S. (Young et al., 1997; Lam, 1998). We also obtain more recent data from the 2000 Finnish Health Survey [data described in Heistaro (2008, p. 118)]. Based on these data, we observe the onset risk to peak in October and November, with a decline during December and another peak in January, after which onset risk starts to decline.

We now investigate aggregate patterns in trading volume. Figure 5 shows 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 result is a clear seasonal pattern: trading volume declines for both individuals and institutions significantly in 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 become apathetic, as pointed out by Kelly and Meschke (2010). However, this is not what we observe for the full sample, nor do we find 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 (correlation coefficient of 0.66-0.67) as well as institutions (correlation coefficient of 0.45-0.46), indicating that people trade less when the day is longer. The unconditional relation is unrelated to latitude, congruent with the holiday hypothesis.

In sum, the descriptive analysis lends little support to the SAD hypothesis. Instead, the aggregate evidence from seasonal trading patterns is by and large consistent with the holiday hypothesis.

4.2. Daily panel regressions

Table 2 reports descriptive statistics for the variables used and Table 3 shows the results for panel regressions with four specifications for *buy ratio* with three investor groups. The coefficient estimate for the *sunniness* variable is close to zero for all investor groups. We also fail to find evidence on the impact of *sunniness* on the *buy ratio* in alternative, more lenient specifications discussed in Section 5.

Perhaps surprisingly, the highest value (0.0017) is for financial corporations, implying a 1.7 percentage point increase in the *buy ratio* when going from a full cloud cover to clear skies. The corresponding effect for nonfinancial corporations is 0.9 percentage points. These effect sizes are similar to that of Mondays, which decrease the *buy ratio* by 0.6 to 2.5 percentage points, depending on investor group. The impact of sunny weather is not statistically significant, however: the highest *t*-statistic is 1.4 for nonfinancial corporations. Furthermore, the effect is the smallest for individual investors (0.2 percentage points), the group of investors that is thought to be the most susceptible to the influence of variations in mood.

Of the other weather variables, the results in Table 3 have the correct sign for *precipitation* (-) in the *buy ratio* regressions. The sign for *temperature* (+) we detect for all three investor groups is inconsistent with the negative stock return effect found in Cao and Wei (2005). The negative precipitation effect is significant for individuals and financial corporations. The data loss in this specification (column 4) is due to only about 20% of the weather stations recording precipitation. The estimated coefficient for *precipitation* implies quite sizable effects. For example, consider a day with precipitation of 10 millimeters (0.4 inch) above the average daily amount of 1.4 mm. This corresponds to a typical amount in a rainy day. The *buy ratio* of individuals would then be 1.9 percentage points below the mean. The effect is even larger for financial corporations at 3.8 percentage points. Including *precipitation* also drives out any effect there was due to the *sunniness* variable. These results imply a significant effect from going from clear skies to full cloud coverage with rain. However, the majority of the effect is produced by rain, not by lack of sunlight.

The calendar control variables are all relevant for trading behavior, but their statistical significance, as well as the direction of influence, varies according to investor group. Individual investors and nonfinancial corporations engage in significant selling on Fridays. Financial corporations sell heavily on Mondays. The other two investor groups also do this, but the effect is not statistically significant for them. The fact that all three groups of investors trade in the same direction on Mondays implies that the omitted group, foreign investors, are net buyers on Mondays. Individual investors buy stocks heavily 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.

In the third column of Table 3, we also report results for a subsample containing a variable indicating whether primary schools (grades 1 through 9) in the municipality were closed. Virtually all of the variation is due to differences in school schedules, rather than unscheduled school closings (e.g., due to bad weather), which are extremely rare in Finland.[16] Hence, we dub this variable *vacation*. The results show that financial institutions reduce their trading activity by 7% when schools are out, but there are no other significant effects in the data. A failure to find an effect for individuals could be due to measurement error and lack of statistical power. First, whereas a bank's trader is very unlikely to trade on the bank's account when he or she is on vacation, individual investors are not similarly constrained. Second, individuals might not be switching between trading mode and abstaining completely from trading in perfect congruence with school holidays. In this case, our identification that is only utilizing the small differences in

[16] Finland does not experience tornadoes or hurricanes, but snowstorms causing traffic problems are possible. However, schools still stay open and students as well as teachers are present.

school schedules between the municipalities, and controlling for lower frequency effects with month fixed effects, could be missing the effect. Thus, it seems that only the longer holiday seasons are relevant for aggregate trading activity, as indicated by the descriptive analysis earlier. Consistent with our evidence on decreased trading by financial institutions when employees are more likely to be absent, McTier, Tse, and Wald (2013) find lower turnover following flu outbreaks in the U.S., and Shive (2012) documents a decrease in local trading for stocks whose headquarters are hit by a power outage.

Combining the results for individual investors selling on Fridays and prior to national holidays with the earlier aggregate results indicating selling prior to vacation periods, we see a pattern of portfolio cleanup before breaks in these two distinct analyses. Financing consumption could explain this pattern for longer holidays, such as summer vacations. However, it cannot be a complete explanation since a three-day settlement lag prevents immediate use of Friday sale proceeds. Reducing the need to monitor investments will not do as an explanation either, as markets will be closed during such periods. A need for mental closure is one potential candidate explanation, applying equally to shorter and longer breaks. Our result for vacation periods is consistent Schmittmann et al. (2015), who find German retail investors and especially the less active individual investors to trade less when the weather is good and the opportunity cost of spending time trading indoors is high.

4.3. Overall economic significance

To facilitate the assessment of overall economic significance, the bottom part of each panel in Table 3 presents adjusted R-squared figures from three different models: containing municipality fixed effects only, municipality and month fixed effects, and the full model. Time effects add the most explanatory power for individual investors. Comparison of the full model to the one with municipality and time-fixed effects shows that the traditional calendar effects and the mood variables collectively only slightly enhance the R-squares: the improvement is 0.1 to 0.2 percentage points in the baseline model. As an alternative measure, we first subtract the sum of squares explained by municipality and month-fixed effects, and then look at the percentage of remaining variation explained. Even when using this alternative measure, the traditional calendar effects and the mood variables together in the baseline model only explain less than 1% of the remaining variation in the *buy ratio* for individual investors, and about 2% for the other investor groups.

Also in the sample of active retail investors of Schmittmann et al. (2015), the coefficient magnitudes imply that mood effects are economically minor at best. For example, in their main specification (Table IV), an increase of one degree Celsius implies a 0.0002 point higher *buy ratio*. In comparison, *Monday* has over 50 times greater impact on the direction of trade than one degree Celsius (reported in their technical appendix TA.I).

4.4. Cross-sectional regressions

In this section, we test the SAD hypothesis (direction of trade is related to length of day) using 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 sunniness. For tests of SAD, we exclude weeks just around each equinox (weeks 12-14 and 38-40) when the length of day is close to 12 hours in the entire country.

Table 4 reports descriptive statistics and Table 5 shows the estimation results. Overall, the results provide some support for SAD affecting the direction of trade for individuals: 53% of daily regressions have a positive coefficient on the *length of day*, and this is statistically significantly different from 50% (*Z*-value = 2.4). However, the corresponding figure from weekly regressions (52%) is insignificant.

The coefficients for financial corporations' daily *buy ratio* regressions have negative signs both on the *length of day* and *sunniness* (*t*-values of -3.04 and -2.21, respectively), which could be interpreted as a liquidity provision to mood-induced investors.

Evidence for the impact of weather on trading decisions is somewhat weaker than that of SAD, as shown by the coefficients for *sunniness* in Table 5. 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. This is also motivated by Watson (2000, p. 95): "It is possible … that significant mood effects can be identified only when more extreme weather phenomena are examined." 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 53% of regressions, which is not statistically significantly different from 50%. For nonfinancial and financial corporations, the coefficient for the *excess buy ratio* regression is positive 51%-52% of the time, although not statistically significant.

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 versus male prevalence of SAD (e.g., Hellekson, 1989). Motivated by these findings, in Table 7 we report cross-sectional results for both men and women. In line with the medical literature, the results are stronger for women with 52% of positive coefficients (vs. 51% for men) for a daily *excess buy ratio* regression, but the difference is not statistically significant. However, we find the opposite pattern in weekly data.

Overall, the results from the cross-sectional analyses reported in Tables 5-7 do not show robust support for the impact of sunniness and the length of day on the direction of trade.

5. Robustness and additional analysis

In this section, we outline robustness checks and additional analyses. In headings, “P” refers to a robustness check or additional analysis on panel regression results and “C” refers to cross-sectional results. All these results are tabulated in a separate Internet-appendix.

5.1. Raw buy ratio without detrending (C)

In Internet Appendix 2 we report the results for the raw buy ratio without detrending on municipality level for the cross-sectional specification in Table 5. The results do not alter our main conclusions using the *excess buy ratio*.

5.2. Using trading volume as dependent variable (P and C)

Our main analysis has focused on the *buy ratio* since the theoretical link between mood and the direction of trade is clear: conditional on trading, an individual who is in a positive mood is more likely to buy rather than sell. Although not extensively discussed in the literature [see Hong and Yu (2009) for an exception], overall trading volume may also be related to investor mood. People on a positive mood are more energetic and might be more likely to trade. On the other hand, the nice weather that contributed to the positive mood might lure them to activities other than trading. We compute trading volume by summing up the number of trades and take the natural logarithm for a measure of trading volume.

In Internet Appendix 3, we reproduce the panel regression analyses of Table 3 and cross-sectional analyses of Tables 4-7 by using *Ln*(*Number of trades*) (Table 3) or excess *Ln*(*Number of trades*) (Tables 4-7) as dependent variable instead of *excess buy ratio*. Excess *Ln*(*Number of trades*) in municipality *i* on day or week *t* is measured analogous to the *excess buy ratio* defined in Section 3:

$$Excess\,Ln(Number\,of\;trades)_{i,t} = a_i + b_i^1 T + b_i^2 T^2 + e_{i,t}\,. \tag{6}$$

For all investor groups, trading volume increases significantly around the turn of the year, and decreases on Mondays. These results complement the large literature on calendar patterns in stock returns. Prior papers on calendar effects rarely analyze trading behavior. In addition, we find some evidence that individuals trade less when the weather is relatively warm and sunny while financial corporations abstain from trading when schools are not in session. However, for contribution to overall R-squared, municipality fixed effects go a long way in explaining variation in trading volume.

Longer days are associated with higher trading volume for all investor groups in both weekly and daily data in the cross-sectional specification results reported in Table 5. The coefficients are positive in 51%-59% of the volume regressions and statistically significant in five of the six daily specifications. Financial corporations also seem to trade less on sunnier days: the coefficients in the volume regression are positive in only 46% of the daily regressions. In sum, there is evidence that longer days are associated with increased trading activity for individuals and decreased volume for professionals.

5.3. Using lagged dependent variable (P)

Our dependent variable of interest (*buy ratio*) may be persistent. 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 Internet Appendix 4, we add the lagged dependent variable to the panel regression, and find that this has little effect on the results.

5.4. Using leading independent variable (P)

The 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 panel regressions including a lead (tomorrow's value) of the explanatory variables. It is, of course, impossible for realized future weather to 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 trading 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 some very nice weather is in store for Friday, might plan her work schedule so that she is able to leave work early 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 weather, as well as a proxy for weather-related expectations. We find that an (unreported) *F*-test for the sum of the coefficients (current and lead) does not lead to material changes in inference compared to the baseline analysis. These results for leading weather variables are reported in Internet Appendix 5.

5.5. Using lagged independent variable (P)

We also investigate potential lagged weather effects.[17] Including the lagged value generally increases the significance of *sunniness*. The lagged weather results are reported in Table 3A of Internet Appendix 6 and do not alter our conclusions.

Some regressors, such as *sunniness* and *temperature*, as well as the dependent variables, are likely to contain persistent shocks. 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. As a check of robustness, we estimate a panel data model that allows contemporaneous correlations between municipalities, and includes a common autoregressive (order one) error process in the time dimension. The results are reported in Table 3B of Internet Appendix 6. 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 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.

[17] The evidence in the psychology literature of a possible lagged effect of weather 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.

5.6. Leaving out calendar control variables (P)

In analysis reported in Internet Appendix 7, we run all the regressions with only *sunniness* 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 (e.g., suppose that during our sample period, Mondays would happen to be cloudier than other days), the estimates for the mood variables might be stronger without controls. But if the mood effects are genuine, controlling for the known seasonal effects (as we do in the baseline regressions) should lead to more precise estimates for the mood variables. We find that the *t*-statistics for the mood variables are indeed slightly lower when we drop the seasonal controls, but the differences to the baseline specification are not significant.

5.7. Cross-sectional clustering of standard errors (P)

In the baseline results in Table 3, we compute standard errors using time-clustering. Alternatively, cross-sectional (municipality level) clustering could be used. In Internet Appendix 8, we report results that have standard errors 2-4 times lower compared to those obtained with time clustering in baseline Table 3, 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. Only time-clustering accounts for cross-correlation induced by non-independent weather variables across municipalities, which is the reason we report baseline results in Table 3 with time-clustering.

5.8. Including SAD variable in a panel regression (P)

In the baseline results of Table 3, we did not include a variable for SAD in the regression as it is a deterministic, slow-moving variable. If we nevertheless include a SAD variable in the regression, it gets an insignificant coefficient, as shown in Internet Appendix 9.

5.9. Subsample analysis (P)

To potentially identify subsamples with stronger mood effects, we report in Internet Appendix 10 panel results for individual investors by gender (Panels A and B), age (Panels C and D), volatility of the traded stock (Panels E and F), and investor trading frequency (Panels G and H). There are minor differences between subsamples (women are more affected by *temperature* and less by *precipitation*; young individuals and occasional traders are slightly more affected by *temperature*). However, the overall conclusion for all subgroups does not change: mood effects, if any, are minor at best.

5.10. Including equinoxes and only fall and winter weeks (C)

We re-estimate the cross-sectional results of Table 5 for *length of day* including all six weeks around equinoxes. The results estimated with these weeks in the sample reported in Internet Appendix 11 are virtually identical. We also estimate the length of day regressions using only weeks between the equinoxes (1-11 and 41-53) due to a practice in medical research on SAD to concentrate generally on the fall and winter seasons. The results are very similar to those reported in the baseline results in Table 5.

5.11. Pure time series regression (P)

We also collapse the panel data into a pure time series structure by aggregating the buy ratios of individual investors throughout the country each day. This analysis allows a cleaner identification for all the variables that lack any cross-sectional variation, such as the calendar effects. The results are presented in Internet Appendix 12. In line with the panel results using time clustered standard errors, the two significant effects are buying in the *first five days of the year* and selling on *Fridays (and before other holidays*). Both effects are also economically significant. If

Friday as the last working day of the week is associated with a better mood on average, then the fact that investors are selling on Fridays is inconsistent with the mood hypothesis. It could be seen as consistent with the holiday hypothesis, however. Although Friday selling does not help finance consumption due to a settlement lag, a smaller position in stocks during time off may help investors to relax by providing mental closure when "gone fishing."

The calendar month dummies allow further insight into the lower frequency variation over the year. Consistent with "sell in May and go away" strategy (Bouman and Jacobsen, 2002), the *buy ratio* is significantly lower in May, with selling continuing in June. Investors then start buying back stocks in July, and do most of that in September and October. This is consistent with the other part of the "sell in May" strategy, i.e., "buy back on St. Leger's day" (in September, the British version of the adage) or, as in the U.S. version, by the time of Halloween (in late October). As noted earlier, this pattern also corresponds to selling before the summer holiday season in Finland and buying back afterwards.

6. Conclusion

Finland provides a great setting for testing whether weather-induced mood has a significant impact on investors' trading behavior. Based on our results, we cannot conclude that this would be the case. *Sunniness* has the right sign on the direction of trade, but it is statistically insignificant. The same is true for *temperature*. *Precipitation* is strong statistically and economically. We find little evidence of seasonal affective disorder (SAD) affecting the tendency to buy versus sell, but there is evidence of a positive effect on the volume of trade.

We do find other clear seasonal patterns in the data, however. But rather than being driven by environmental mood variables, they seem to align with holiday seasons. The results show that investors trade less during holiday periods overall, and tend to sell prior to them. The need to finance vacation-related consumption could explain the patterns around summer holidays ("sell in May/buy back by Halloween" effect), but a more refined hypothesis is probably needed to explain selling ahead of weekends and other short holidays.

Magnitudes on the impact of the classical calendar effects on trading are comparable to price effects. For example, Tetlock (2007) quantifies the sentiment expressed in *The Wall Street Journal's* daily market commentary and finds that a one standard deviation change in sentiment affects the next day's market returns by 4-8 basis points, which is of similar magnitude as the Monday effect (Wang, Li, and Erickson, 1997) and the weather effect (Hirshleifer and Shumway, 2003). In this paper we document that Mondays and weather-related mood variables have a roughly similar impact on trading behavior. The Monday effect thus serves as a useful benchmark: the impact of the day-to-day changes in sentiment is similar to the Monday effect when it comes to both stock returns and trading behavior. By way of Bayesian statistical inference, a reasonable prior might be that the classical seasonal effects are real. Hence, the weather-related mood effects could turn out statistically significant when being evaluated jointly across multiple samples in future studies.

The total impact of all the weather-related mood variables as well as the traditional calendar effects combined, as evidenced by their contribution to model adjusted R-squared, is very small, however. Thus, 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 on a population level. However, it is possible that in subsets of individual investors, mood effects do play some role in trading decisions as reported by

Schmittmann et al. (2015). Both their and our results share the same theme: the overall magnitude of the mood effect on trading is weak at best.

Lack of finding mood-driven variation in day-to-day trading behavior does not imply that investor sentiment can be ignored more broadly. Different mechanisms are likely to be 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, García, 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 researchers argue that the market effects are brought about 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.[18] 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. Along the lines of this paper, where we have limited our study to weather-related mood variables, an analysis applied to these discrete events would also be interesting.

To our knowledge, we are the first to study the effect of mood on trading behavior in a setting with significant geographic and time series variation in amount of sunlight and weather. However, we may not be aware of unpublished work finding weak results between mood and trading

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[18] Strictly speaking, sudden changes in weather do represent discrete changes. However, contrary to major sporting events or disasters, such effects are still normally very mundane. This is especially true in Finland where there are no hurricanes or tornadoes.

behavior, or no results between other potential environmental factors and asset prices, given that many well-crafted papers with no significant results may end up unpublished.

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Table 1
Descriptive statistics on the investor data

This table reports 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: Investors and trades in the base sample

	Number of investors / trades
Domestic investors	1,178,333
Individual investors	1,119,406
Institutional investors	45,855
Nonfinancial corporations	45,102
Financial corporations	753
Trades by domestic investors	
Individual investors	7.2 million
Institutional investors	
Nonfinancial corporations	2.34 million
Financial corporations	3.49 million

Panel B: Municipalities

	Number of municipalities
Municipalities in Finland in 1995	455
Removed from sample due to merger	10
Removed from sample due to less than five trades on all trading days	1
Municipalities in the sample	444

Table 2

Descriptive statistics at 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 five trades by the investor group on the given day. Panel A presents statistics for the dependent variables in a municipality/day cell, which is the unit of observation. Panel 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 ratio* is defined as # of buys / (# of buys and sells). *Sunniness* takes the value of 1 for days when sky cannot be observed and 10 for clear sky. *Last 5 trading days of the year*, *First 5 five trading days of the year*, *Monday or after holiday*, *Friday or before holiday*, and *Last 3 and 1st trading day of month* are self-explanatory calendar dummy variables. *Precipitation* is the amount of rain in mm. *Vacation* is a dummy indicating if 1st to 9th grade primary schools were closed in the municipality on the trading day.

	Low	Mean	Median	High	St. Dev.	Skewness	Kurtosis	N
Panel A. Dependent variables								
Individuals								
Buy ratio	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 ratio	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 ratio	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 B. Independent variables								
Sunniness (index)	1.00	4.23	3.00	10.00	2.55	0.86	2.32	200,597
Last 5 trading days of year	0	0.02	0	1	0.15	6.55	43.85	200,597
First 5 trading days of year	0	0.03	0	1	0.16	6.03	37.33	200,597
After holiday dummy	0	0.21	0	1	0.41	1.41	2.98	200,597
Before holiday dummy	0	0.23	0	1	0.42	1.31	2.72	200,597
Turn of the month dummy	0	0.17	0	1	0.38	1.75	4.06	200,597
Temperature, Celsius	-44.40	6.16	5.20	31.80	10.41	-0.12	2.63	200,597
Precipitation, mm	0	1.65	0.40	44.90	3.07	3.78	25.18	39,386
Vacation	0	0.25	0	1	0.43	1.13	2.28	105,925

Table 3

Buy ratio: Panel regressions for weather-related mood variables and calendar effects

The depended variable is *buy ratio* based on trade count. 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 into domestic individuals, nonfinancial corporations, and financial corporations. To enter the sample, the municipality must have at least five trades by the investor group on the given day and be in the sample of 444 municipalities (10 municipalities are excluded due to merger, additional missing municipalities due to having fewer than five trades). *Sunniness* takes the value of 1 for days when sky cannot be observed and 10 for clear sky. *Last 5 trading days of the year, First 5 five trading days of the year, Monday or after holiday*, *Friday or before holiday*, and *Last 3 and 1st trading day of* month are self-explanatory calendar dummy variables. *Temperature* (Celsius) and *Precipitation* (millimeters) are demeaned by subtracting the municipality's average for that week of the year. *Vacation* is a dummy indicating if 1st to 9th grade primary schools were closed in the municipality on the trading day. All specifications include municipality and month fixed effects as well as a constant term, and they are estimated with OLS. Absolute values of *t*-statistics based on standard errors clustered at the daily level are reported below coefficients. Adjusted R-squared figures are reported for three different models: using only municipality fixed effects (*Muni FE Only*) on the same sample as the reported specification, using municipality and each month-fixed effects (*Muni and time FE*), and for the full model for which the coefficients are shown in the table (*Full model*). *Increase, pp.* gives the improvement in the adjusted R-squared in percentage points when going from *Muni and time FE* to *Full model*. *Remaining var. explained* gives the adjusted R-squared for the full model after subtracting the sum of squares explained by municipality and month-fixed effects. *, **, and *** denote significance (2-tailed) at the 10%, 5%, and 1% levels, respectively.

Panel A: Individuals				
variable	(1)	(2)	(3)	(4)
Sunniness	0.0002	0.0002	0.0002	-0.0001
	0.435	0.413	0.417	-0.100
Last 5 days of year	0.0022	0.0027	0.0052	-0.0076
	0.156	0.192	0.351	-0.493
First 5 days of year	0.0378**	0.0374**	0.0382**	0.0311
	2.538	2.513	2.439	1.617
Monday or after holiday	-0.0064	-0.0064	-0.0066	-0.0041
	-1.384	-1.378	-1.34	-0.681
Friday or before holiday	-0.0177***	-0.0177***	-0.0151***	-0.0144**
	-3.234	-3.231	-2.704	-2.078
Last 3 and 1st day of m.	-0.0039	-0.0038	-0.005	-0.0057
	-0.769	-0.759	-0.95	-0.857
Temperature (demeaned)		0.0002	0.0004	0.0009
		0.535	1.133	1.562
Vacation			-0.0046	
			-0.76	
Precipitation (demeaned)				-0.0019***
				-3.057
Number of observations	200,597	200,597	105,925	39,386
Number of municipalities	444	444	236	144
Adj. R^2 for:				
- Muni FE only	0.028	0.028	0.033	0.029
- Muni and time FE	0.115	0.115	0.124	0.124
- Full model	0.116	0.116	0.125	0.125
Increase, pp.	0.001	0.001	0.001	0.002
Remaining var. explained	0.9%	1.0%	0.8%	1.3%

Panel B: Nonfinancial corporations				
variable	(1)	(2)	(3)	(4)
Sunniness	*0.0009*	*0.0008*	*0.0007*	*-0.0003*
	1.443	1.326	0.931	-0.189
Last 5 days of year	*0.0073*	*0.0095*	*0.0108*	*0.0115*
	0.553	0.72	0.651	0.527
First 5 days of year	*0.0053*	*0.0035*	*0.0017*	*0.0051*
	0.339	0.226	0.097	0.267
Monday or after holiday	*-0.0067*	*-0.0066*	*-0.0026*	*-0.0112**
	-1.556	-1.538	-0.516	-1.725
Friday or before holiday	*-0.0158****	*-0.0156****	*-0.0168****	*-0.0142***
	-3.556	-3.529	-3.3	-2.142
Last 3 and 1st day of m.	*-0.0109***	*-0.0108***	*-0.0153****	*-0.0096*
	-2.352	-2.325	-2.861	-1.428
Temperature (demeaned)		*0.0009***	*0.0010***	*0.0020****
		2.198	2.136	2.897
Vacation			*0.0019*	
			0.262	
Precipitation (demeaned)				*-0.0006*
				-0.722
Number of observations	44,488	44,488	25,259	11,173
Number of municipalities	354	354	191	107
Adj. R^2 for:				
- Muni FE only	0.026	0.026	0.024	0.037
- Muni and time FE	0.039	0.039	0.040	0.053
- Full model	0.040	0.040	0.041	0.054
Increase, pp.	0.001	0.001	0.001	0.001
Remaining var. explained	2.0%	2.5%	2.9%	2.2%

Panel C: Financial corporations				
variable	(1)	(2)	(3)	(4)
Sunniness	*0.0017*	*0.0016*	*0.0023*	*-0.0023*
	1.157	1.097	1.255	-0.577
Last 5 days of year	*-0.1028****	*-0.1018****	*-0.0547*	*-0.1093***
	-3.728	-3.69	-1.622	-2.517
First 5 days of year	*-0.0047*	*-0.0057*	*0.0565*	*0.006*
	-0.16	-0.194	1.323	0.156
Monday or after holiday	*-0.0252****	*-0.0251****	*-0.0204**	*-0.0272**
	-2.952	-2.94	-1.941	-1.815
Friday or before holiday	*0.0004*	*0.0006*	*-0.0108*	*-0.0182*
	0.05	0.07	-1.022	-1.225
Last 3 and 1st day of m.	*-0.0035*	*-0.0035*	*-0.0215**	*-0.0024*
	-0.395	-0.392	-1.846	-0.147
Temperature (demeaned)		*0.0006*	*0.0003*	*0.0002*
		0.607	0.201	0.109
Vacation			*-0.0076*	
			-0.443	
Precipitation (demeaned)				*-0.0038***
				-2.106
Number of observations	6,866	6,866	3,544	2,008
Number of municipalities	174	174	87	52
Adj. R^2 for:				
- Muni FE only	0.083	0.083	0.107	0.100
- Muni and time FE	0.093	0.093	0.123	0.113
- Full model	0.095	0.095	0.125	0.116
Increase, pp.	0.002	0.002	0.001	0.003
Remaining var. explained	2.2%	2.1%	1.0%	2.4%

Table 4
Descriptive statistics for cross-sectional analysis

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 are used in the cross-sectional regressions with data described and results reported in Table 5.

	Min	Mean	Median	Max	St. Dev.	Skewness	Kurtosis	*N*
Individuals								
Excess buy ratio	-0.91	0.00	-0.01	1.13	0.36	0.06	1.97	444,704
Sunniness (index)	1.00	4.28	3.00	10.00	2.55	0.83	2.28	444,704
Length of the day (hours)	0.00	12.47	12.30	24.00	5.07	0.05	1.86	444,704
Nonfinancial corporations								
Excess buy ratio	-1.02	0.00	0.01	1.06	0.39	-0.08	1.66	128,718
Sunniness (index)	1.00	4.33	3.00	10.00	2.57	0.79	2.21	128,718
Length of the day (hours)	0.00	12.27	12.02	24.00	4.98	0.10	1.87	128,718
Financial corporations								
Excess buy ratio	-1.04	0.00	-0.01	1.03	0.39	0.06	1.76	20,612
Sunniness (index)	1.00	4.34	3.00	10.00	2.57	0.79	2.21	20,612
Length of the day (hours)	1.34	12.42	12.29	24.00	4.79	0.03	1.73	20,612

Table 5
Excess buy ratio: Cross-sectional regressions for SAD and sunniness

Results for the binomial *Z*-test for the impact of amount of *Sunniness* (from 1 to 10) and *Length of day* (the number of hours between sunrise and sunset) on direction of trade by investor group. The unit of observation is municipality and day/week. The dependent variable is *excess buy ratio* (see Section 3 for exact variable descriptions) is regressed on *Sunniness* or *Length of day* and a constant. The *Z*-test statistic is computed with the binomial test as (% of positive coefficients when regressing *excess buy ratio* on *Sunniness* or *Length of day* for each municipality –50%) / (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 the 10%, 5%, and 1% levels, respectively.

Panel A: Weekly regressions with excess buy ratio as dependent variable

		Individual	Nonfinancial corporation	Financial corporation
Sunniness	# of regressions during weeks 1-53	403	403	403
	% of positive coefficients	47.1%	50.6%	54.1%
	z-test	*-1.15*	*0.25*	*1.64*
	total # of municipality/week observations	134,502	52,333	9,748
Length of day	# of regressions during weeks 1-53 ex 12-14 and 38-40	356	356	356
	% of positive coefficients	52.2%	53.1%	48.6%
	z-test	*0.85*	*1.17*	*-0.53*
	total # of municipality/week observations	130,720	52,255	9,673

Panel B: Daily regressions with excess buy ratio as dependent variable				
		Individual	Nonfinancial corporation	Financial corporation
Sunniness	# of regressions during weeks 1-53	1918	1918	1915
	% of positive coefficients	49.4%	49.5%	46.5%
	z-test	*-0.55*	*-0.41*	*-3.04****
	total # of municipality/day observations	444,704	128,718	20,612
Length of day	# of regressions during weeks 1-53 ex 12-14 and 38-40	1694	1694	1693
	% of positive coefficients	52.9%	51.3%	47.3%
	z-test	*2.38***	*1.07*	*-2.21***
	total # of municipality/day observations	444,615	133,611	20,112

Table 6

Excess buy-ratio: Cross-sectional regressions with top-quintile sunniness variation

Results for the binomial *Z*-test for the impact of amount of *sunniness* (from 1 to 10) for the top quintile of observation days with most cross-sectional variation in the actual amount of sunniness. 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 the 10%, 5%, and 1% levels, respectively.

Daily regressions with excess buy ratio as dependent variable				
		Individual	Nonfinancial corporation	Financial corporation
Sunniness	# of regressions during weeks 1-53	361	361	315
	% of positive coefficients	52.6%	51.2%	52.2%
	z-test	*1.00*	*0.47*	*0.84*
	total # of municipality/day observations	86,236	25,535	4,157

Table 7
Cross-sectional regressions for SAD by gender

Results for the 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 the 10%, 5%, and 1% levels, respectively.

Panel A: Weekly regressions with excess buy ratio as dependent variable

		Males	Females
Length of day	# of regressions during weeks 1-53	356	356
	% of positive coefficients	53.1%	48.9%
	z-test	*1.17*	*-0.42*
	total # of municipality/week observations	106,015	50,645

Panel B: Daily regressions with excess buy ratio as dependent variable

		Males	Females
Length of day	# of regressions during weeks 1-53	1694	1694
	% of positive coefficients	51.4%	51.9%
	z-test	*1.17*	*1.55*
	total # of municipality/day observations	414,317	216,226

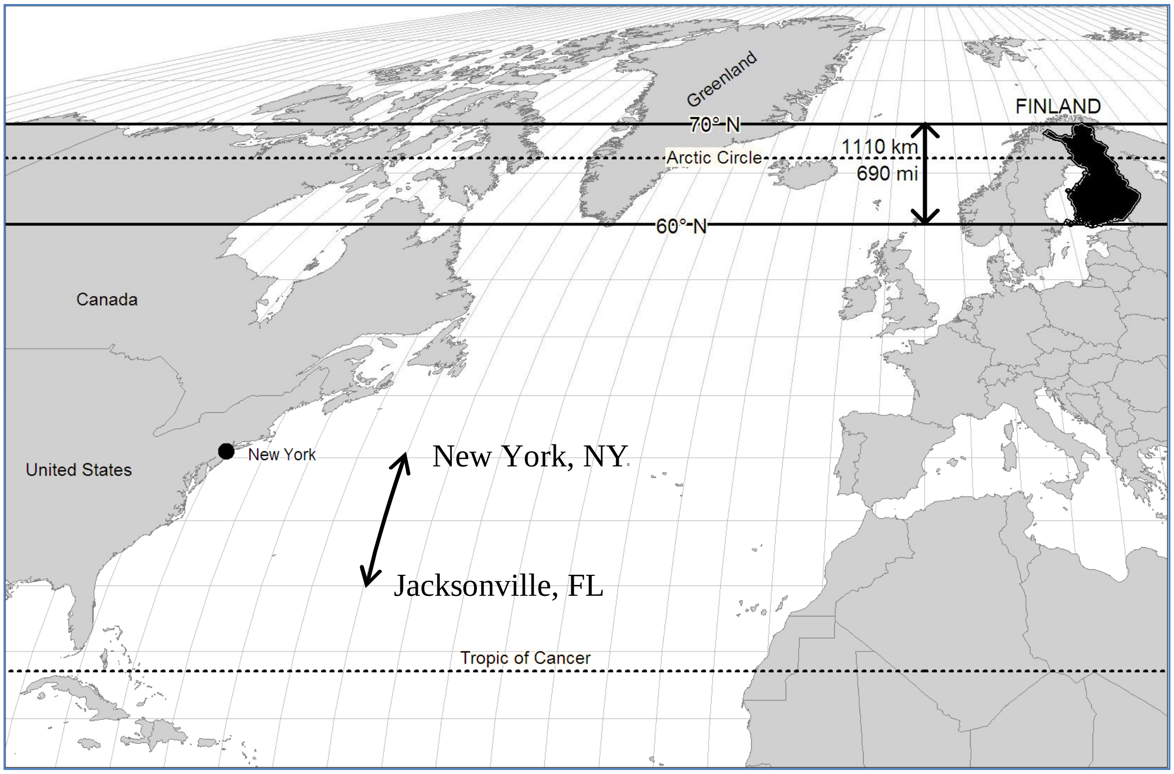


Figure 1. Location of Finland. This figure depicts the Mollweide projection (priority on accurate representation of area rather than direction) of Finland, Europe, and Eastern United States. The vertical distance from the southern tip to the northern tip of Finland (1,110 kilometers, or 690 miles) is approximately equal to the vertical distance from Jacksonville Florida to the New York City.

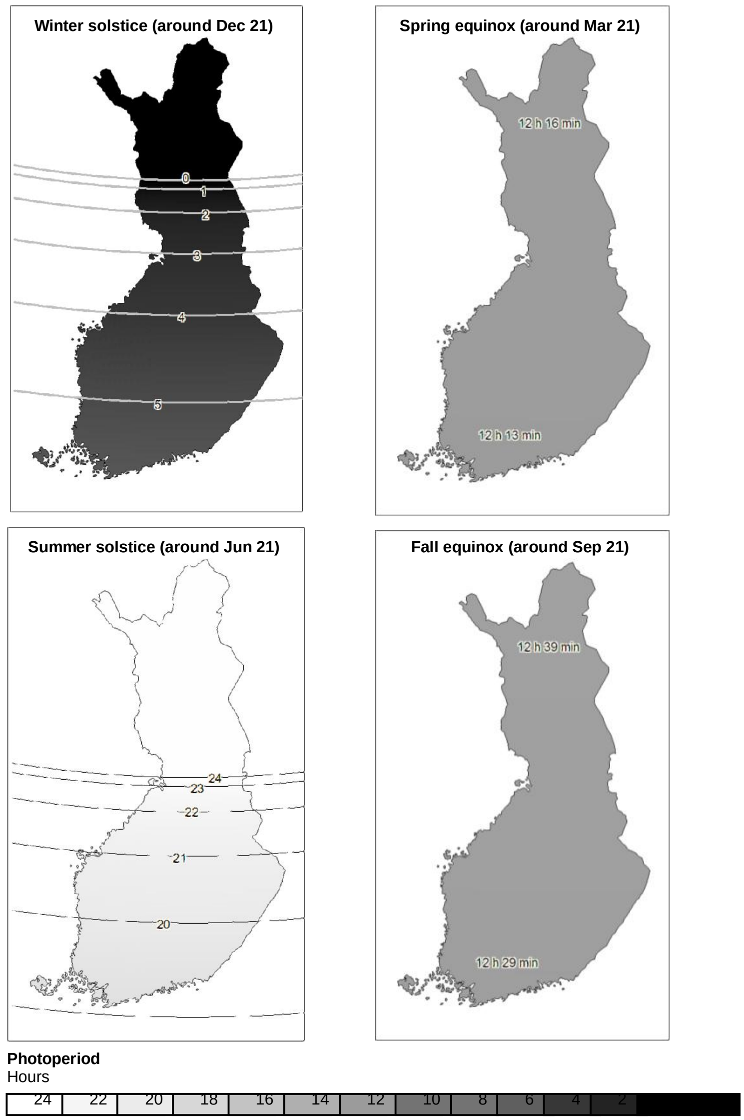


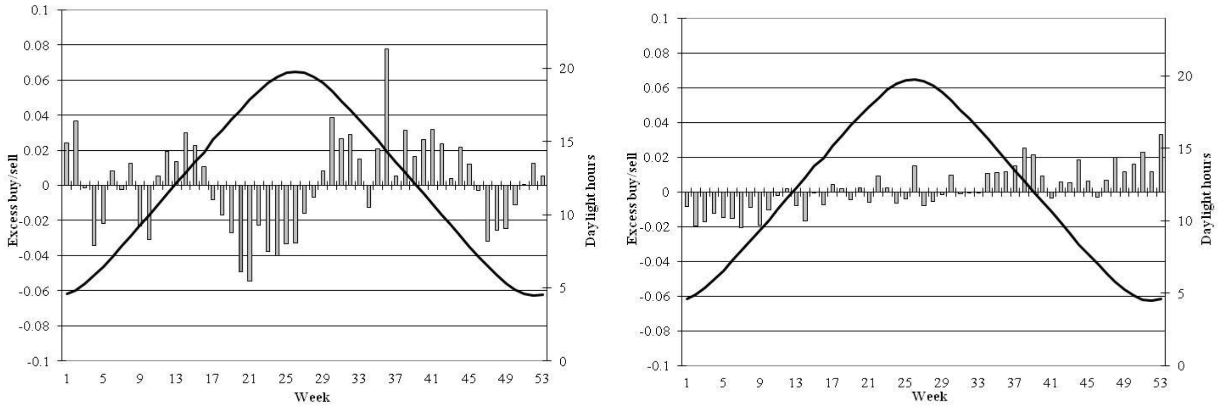
Figure 2. Hours of daylight. Length of day (i.e., time between sunrise and sunset) during winter solstice, spring equinox, summer solstice and fall equinox. The four maps show the length of day in hours with isocurves marking the line for exact hours during the time.

Individuals **Institutions**

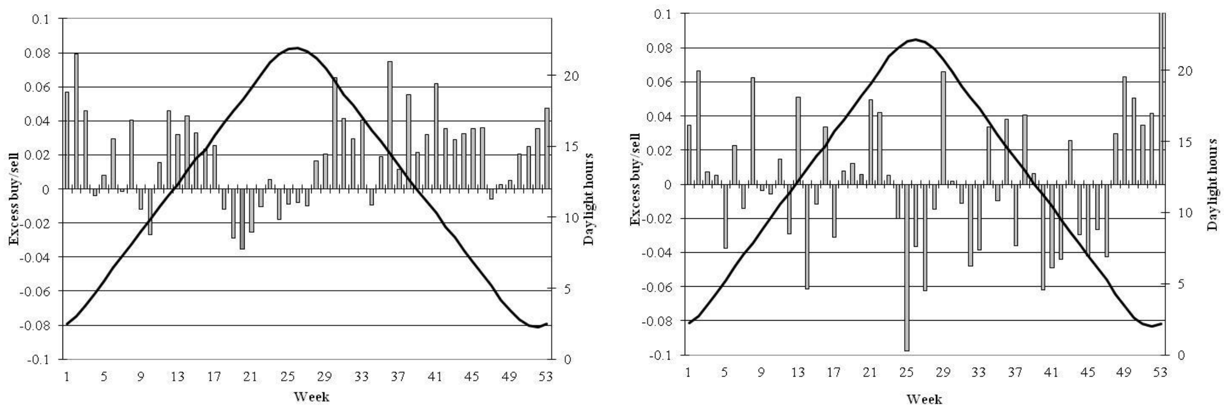
Figure 3. Geographical representation for the number of trades in the sample. The left-hand graph shows the number of trades for domestic individual investors with one dot representing 1,000 trades over the sample period from January 1, 1995 through November 28, 2002. The right-hand figure shows the 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 north latitude)



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



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

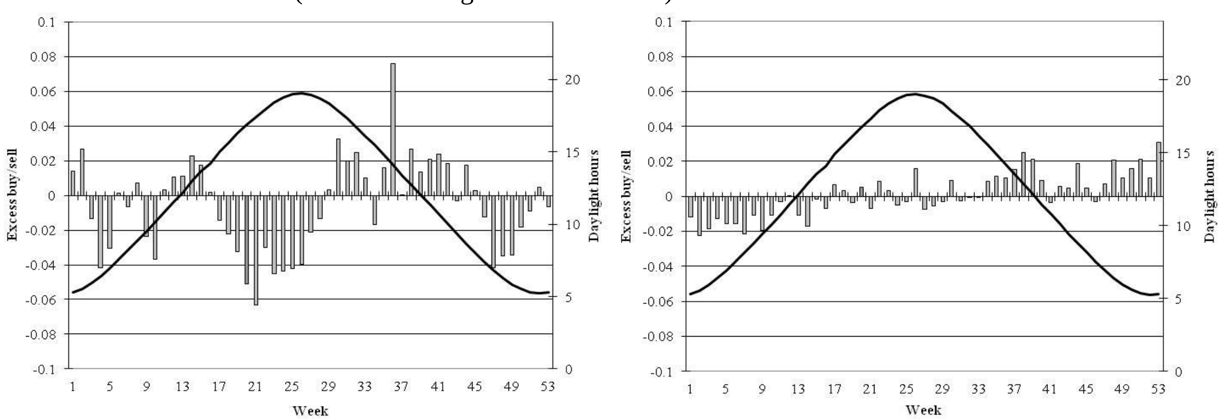
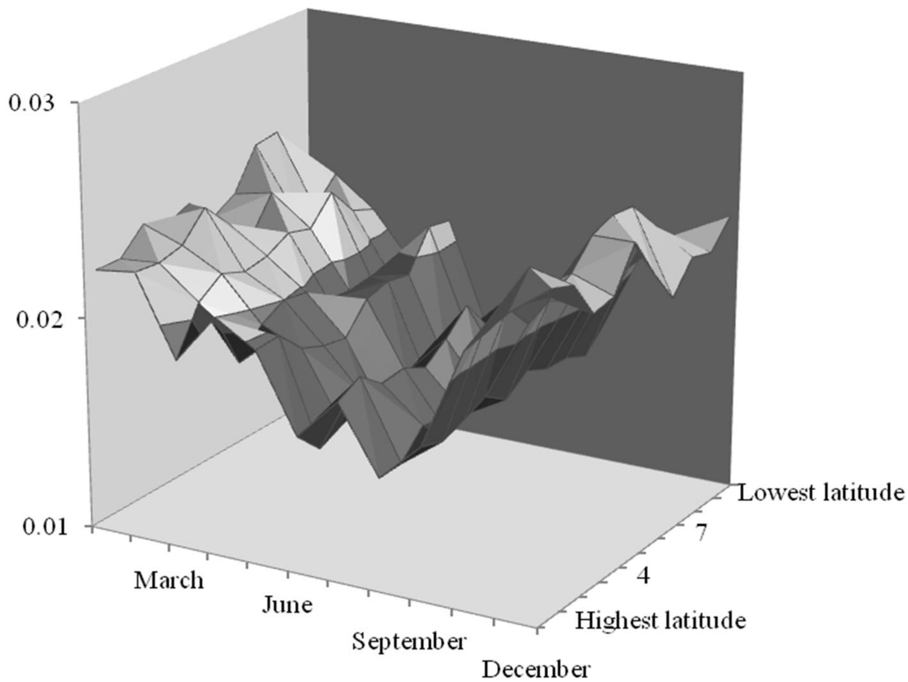


Figure 4. Daylight and abnormal *buy ratio*. The abnormal *buy ratio* is defined as weekly # of buys/(weekly # of buys + weekly # of sells) – annual # of buys/(annual # of buys + annual # of sells). The data include all transactions by domestic investors in Finland. The number of trades for calculating 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

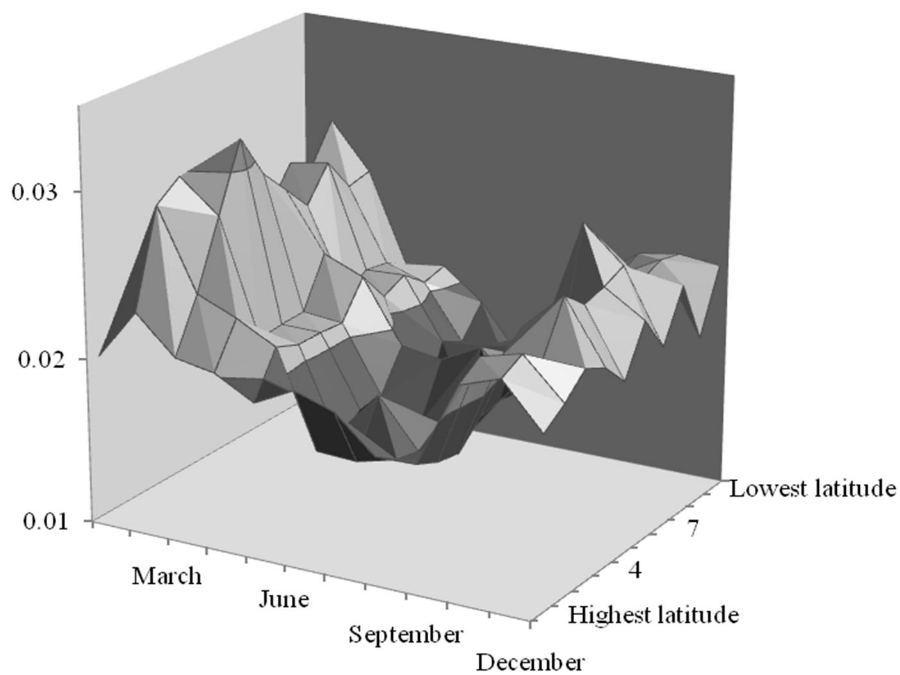
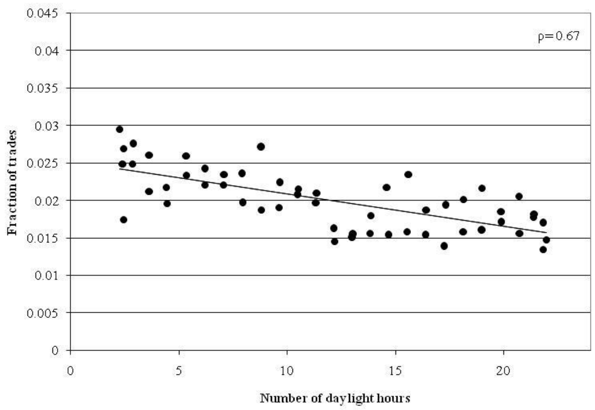


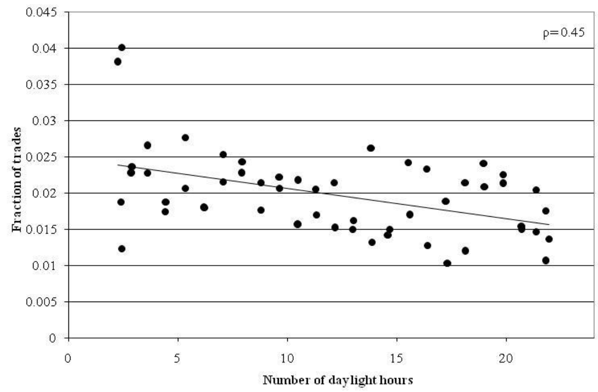
Figure 5. Weekly fraction of trading volume (weekly number of trades/annual number of trades) by month and latitude, based on all transactions by domestic investors in Finland. The number of observations is 170,872 for households and 12,257 for institutions.

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

Individuals

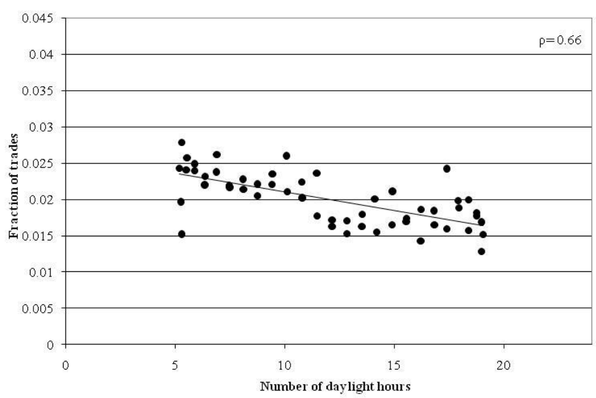


Institutions



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

Individuals



Institutions

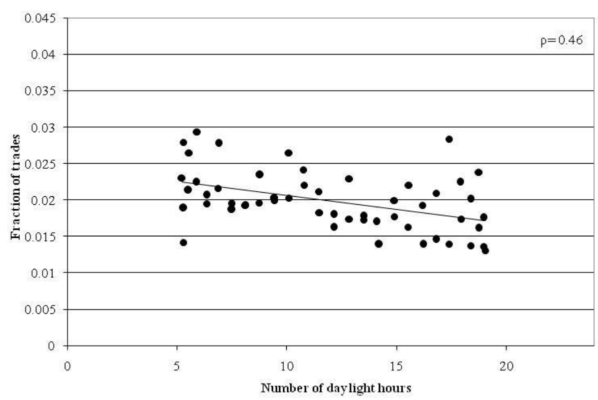


Figure 6. Daylight and volume. The plotted fraction volume is defined as the weekly number of trades/annual number of trades. The analysis includes all transactions by domestic investors in Finland. The scatterplot observations represent the average weekly volume fractions of annual volume. The averages 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).