Predicting anomaly performance with politics, the weather, global warming, sunspots, and the stars

Robert Novy-Marx*

Abstract

Predictive regressions find that the party of the U.S. President, the weather in Manhattan, global warming, the El Niño phenomenon, sunspots, and the conjunctions of the planets all have significant power predicting the performance of popular anomalies. The interpretation of these results has important implications for the asset pricing literature.

Keywords: Predictive regressions, anomaly performance.

JEL Classification: G12, C18.

* Simon Graduate School of Business, University of Rochester, 500 Joseph C. Wilson Blvd., Box 270100, Rochester, NY 14627. Email: robert.novy-marx@simon.rochester.edu.

1. Introduction

Estimating an asset's expected return is a difficult task—sufficiently difficult that Merton (1980) characterizes the attempt as a "fool's errand." He concludes that "even if the expected return...were known to be a constant for all time, it would take a very long history of returns to obtain an accurate estimate." He further suggests that "...if this expected return is believed to be changing through time, then estimating these changes is still more difficult," and that it is consequently "difficult to use the time series of realized returns to distinguish among different models for expected return."

A large literature has nevertheless demonstrated that many economic variables have power predicting the market. A partial list of significant predictors includes short term interest rates (Fama and Schwert, 1977), credit spreads (Keim and Stambaugh, 1986), the term structure slope (Campbell 1987), stock volatility (French, Schwert and Stambaugh, 1987), and the aggregate dividend yield (Fama and French 1988). More recently Baker and Wurgler (2000) find that the equity share of new issuance predicts the performance of the market, while Lettau and Ludvigson (2001) and Lamont and Stein (2004) find similar results using the consumption-wealth-ratio and aggregate short interest.

Variables related to investor sentiment have also been shown to predict asset returns. Baker and Wurgler (2006), Lemmon and Portniaguina (2006), and Stambaugh, Yu, and Yuan (2012) find that investor sentiment, as measured by the University of Michigan survey of consumer sentiment, the Conference Board survey of consumer confidence, and the Baker-Wurgler sentiment index, has significant power predicting the performance of of a number of anomalies. These include strategies related to small, young, volatile and unprofitable stocks, momentum, firms that issue large amounts of equity, and a host of earnings and investment related anomalies. Cooper, Gutierrez and Hameed (2004) find that recent past market performance, an important determinant of investor sentiment, predicts the profitability of momentum strategies. Kamstra, Kramer and Levi (2003) find that cold weather, through its association with depression linked to Seasonal Affective Disorder (SAD) and depression's impact on investor sentiment, predicts market performance.

This paper, inspired by the success of this earlier work, investigates the power that several additional variables have predicting the performance of well known anomalies, and extends the literature in two dimensions. First, it shows that variables known to predict the market, including the party of the sitting president and the weather, have significant power predicting the performance of a host of other trading strategies. Second, and more importantly, it identifies several novel powerful predictors, including global warming, the El Niño phenomenon, sunspot activity, and the conjunctions of the planets.[1]

2. Results

Following the literature, I forecast returns using linear regressions of the form

$$R_t = a + bX_{t-1} + \varepsilon_t, \tag{1}$$

where R_t is the strategy's realized excess return over month t and X_{t-1} is the value of the predictive variable at the start of the month. I investigate this relation, for a variety of anomalies and predictors, using ordinary least squares (OLS) time series regressions. In particular, I test the null hypothesis that $b = 0$, and interpret a rejection of the null as evidence that the explanatory variable has significant power predicting the anomaly's performance.

2.1. Predicting anomaly performance with political parties

The federal government, both through its policies and its operations, has a profound impact on the U.S. economy. It may therefore by reasonable to ask whether the views of the executive, and in particular whether the party in power is business-friendly, affects the performance of assets.[2] This suggests the predictive variable used in the first set of regres-

[1] My results are also related to those of Barro (1989), which considers links between wages and the weather, and to the optimal taxation theory of Mankiw and Weinzierl (2010).

[2] A formal model may be necessary to explain why asset performance should be affected over the course of an administration, as opposed to just the period over which the outcome of the election becomes clear to the market.

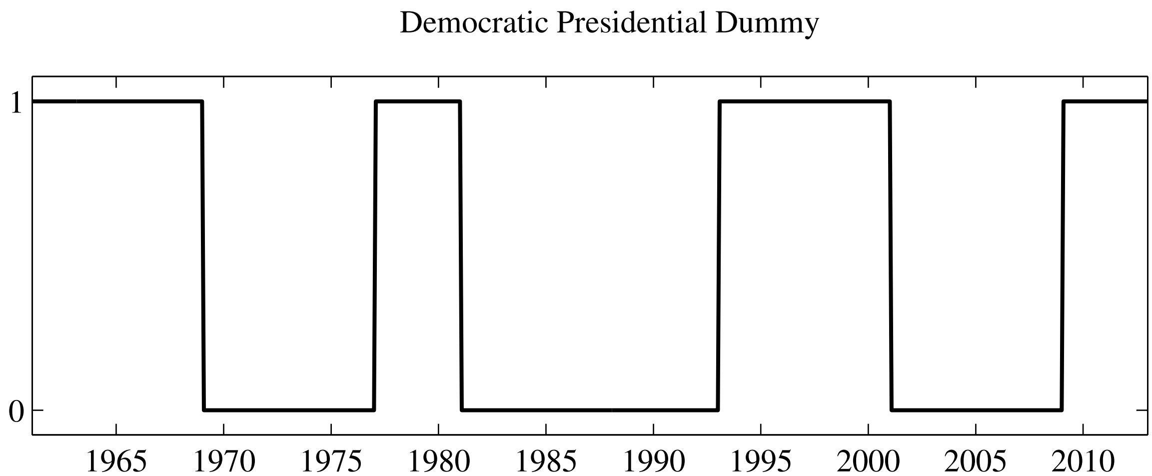

Fig. 1. Democrats in the Oval Office. This figure shows a dummy for Democratic presidents, from January 1961 (Kennedy's inauguration) to December 2012.

sions, a dummy for whether the sitting U.S. President is a Democrat, shown in Figure 1. The sample covers Kennedy's inauguration, in January 1961, through the end of December 2012.

Table 1 shows that since Kennedy took the presidency essentially all of the equity premium, and all of the small cap stocks' outperformance of large caps, can be explained by the party of the sitting president.[3] Over these 52 years the market has only outperformed T-Bills by an insignificant 12 basis points per month in months that begin with a Republican in the Oval Office, but beaten T-Bills by a highly significant 87 basis points per month in months that started with a Democratic Commander-in-Chief. This 75 basis points per month difference is significant at the 5% level.

[3] A list of all the anomalies used in this paper is provided in the appendix. With the exception of the Fama and French (1993) factors, and Frazzini and Pedersen's (2013) betting against beta factor, which come directly from those authors' websites (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library/f-f_bench_factor.html and http://www.econ.yale.edu/~af227/, respectively), all of the anomalies considered in this paper are constructed using a consistent methodology, and come from Novy-Marx and Velikov (2013). They are value-weighted strategies, which buy and sell the extreme deciles (calculated using NYSE breaks) from a sort on some firm characteristic. Strategies based on annual data are rebalanced at the end of June, employing accounting data for the fiscal year ending in the previous calendar year. Strategies based on past stock performance or quarterly accounting data are rebalanced monthly, assuming accounting data is publicly available after quarterly earnings announcements. A more detailed description of the strategies' construction, and the return series for all the anomalies employed here, are available at http://rnm.simon.rochester.edu/data_lib/index.html.

Table 1
The power of presidential party to predict anomaly strategy performance
The table reports results from the following OLS regressions:

$$\begin{aligned} R_t &= m + \varepsilon_t \\ R_t &= a + bX_{t-1} + \varepsilon_t \\ R_t &= a_D X_{t-1} + a_R(1 - X_{t-1}) + \varepsilon_t \end{aligned}$$

where R are the monthly excess returns to an anomaly strategy, and X is a dummy for Democratic presidents. Specifically, the table reports estimated average monthly anomaly excess returns ($\hat{m}$), the sensitivity of anomaly returns to a Democratic President ($\hat{b}$), and the average excess returns to the strategies under Democrats and Republicans ($\hat{a}_D$ and $\hat{a}_R$, respectively). The sample covers January 1961 (the Kennedy inauguration) through December 2012. The strategies based on earnings-to-price and Ohlson's O-score are only available from July 1973, a date determined by the availability of quarterly Compustat data.

Strategy	$\hat{m}$	$\hat{b}$	$\hat{a}_D$	$\hat{a}_R$
Panel A: Strategies that perform significantly better under Democratic Presidents				
Market	0.47	0.75	0.87	0.12
	[2.60]	[2.08]	[3.29]	[0.51]
Size	0.28	0.84	0.73	-0.10
	[1.48]	[2.21]	[2.63]	[-0.41]
Panel B: Strategies that perform significantly better under Republican Presidents				
Earnings-to-price	1.07	-0.99	0.46	1.45
	[5.03]	[-2.27]	[1.36]	[5.37]
Idiosyncratic Volatility	0.36	-1.95	-0.74	1.21
	[1.21]	[-3.23]	[-1.63]	[3.04]
Ohlson's O-score	0.39	-0.81	-0.10	0.71
	[1.97]	[-1.98]	[-0.31]	[2.78]

The second row of Table 1 shows that over the same period the smallest decile of stocks outperformed the largest decile, on a value weighted basis, by 28 basis points per month. This outperformance has, however, come unevenly through time. Small stocks have beaten large stocks by almost three quarters of a percent per month under Democratic presidents, but actually underperformed large stocks by 10 basis points per month during Republican administrations. The 84 basis points per month difference is again significant at the 5% level. These results are consistent with the "presidential puzzle" of Santa-Clara and Valkanov (2003), which documents superior stock market performance during Democratic administrations, especially on an equal-weighted basis, over the period spanning 1927 to

1998 (see also Powell et. al., 2007).

One explanation seemingly consistent with these facts is that Republicans favor big business, which hurts the broader economy. Panel B presents further evidence supporting this hypothesis. It suggests that investors, fearing the performance of the economy as a whole under Republicans, seek the safety of high quality investments. The panel shows that highly profitable stocks, stocks with low volatility, and stocks of firms with low predicted probability of bankruptcy, i.e., exactly the types of stocks an investor would buy in the "flight to quality," perform dramatically better under Republican presidents. The strategy based on earnings-to-price yields excess returns of 1.45% per month under the GOP, more than three times as much as it does under Democratic presidents. The difference, nearly a percent per month, is significant at the 5% level. The strategy that buys low idiosyncratic volatility stocks and sells high idiosyncratic volatility stocks has earned 1.21% per month under the Republicans, but lost 74 basis points per month under Democrats. The difference, almost two percent per month, is significant at the 1% level. The stocks of safer firms, i.e., those most unlikely to go bankrupt under Ohlson's (1980) accounting based predictive model, have also performed significantly better with Republicans in office.

2.2. Predicting anomaly performance with the weather

Kamstra, Kramer, and Levi (2003) offer a plausible mechanism whereby the weather, through its impact on investor risk-aversion, induces predictability in market returns. They propose that increasing levels of depression in the fall, associated with Seasonal Affective Disorder (SAD), increases investor risk aversion. This decreases stock prices, and raises winter yields. Investors' appetite for risk returns in the spring, as winter's depression loosens its grip with the lengthening days, increasing stock prices. This predictable seasonal variation in investor risk tolerance induces predictability in market returns, with higher returns observed over the colder months.

Cao and Wei (2005) find similar empirical results, and also tell a behavioral story, but suggest that the driving factor is *lower* risk aversion in the winter months. They state that

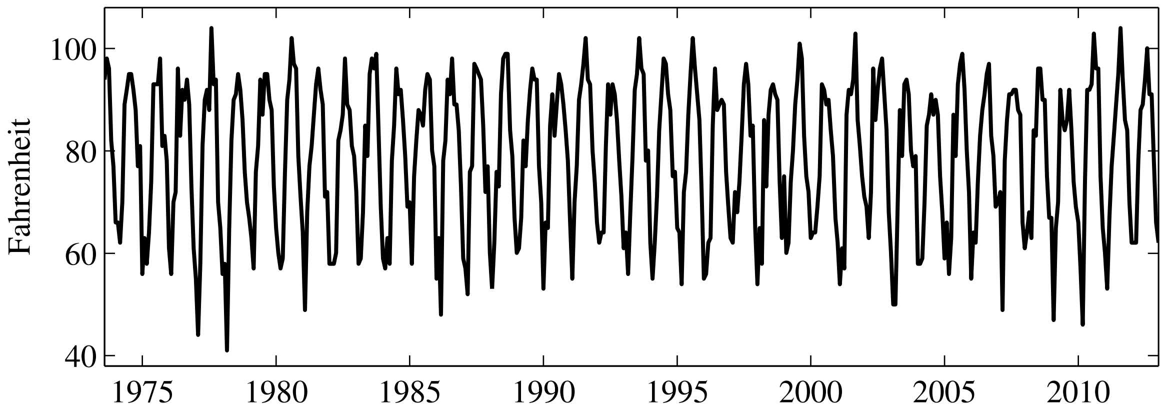

Fig. 2. Monthly maximum temperature in New York City. This figure shows the monthly high temperature recorded at the Central Park weather station, over the period including July 1973 to December 2012.

"lower temperature can lead to aggression... [which] could result in more risk-taking... We therefore expect lower temperature to be related to higher stock returns." Hirshleifer and Shumway (2003), however, present seemingly contradictory results. They claim that "psychological evidence and casual intuition predict that sunny weather is associated with upbeat mood," with the result that "sunshine is strongly significantly [positively] correlated with stock returns."

These results all suggest the predictive variable used in the second set of regressions, the monthly high temperature recorded at the Central Park weather station, shown in Figure 2. I use this location because traders predominately live in the New York Metropolitan area, and it is consequently this weather that should impact their "animal spirits." The weather data come from The National Climatic Data Center (NCDC), and can be downloaded from http://www.ncdc.noaa.gov/cdo-web/search. The data cover July 1973 to December 2012, dates determined by the availability of the quarterly CompuStat data used in the construction of many of the test strategies.

Table 2 shows that New York City weather has significant power predicting the performance of many of the same anomalies as investor sentiment, further suggesting that the weather's influence on anomaly performance operates through its impact on traders' moods. Cold weather in Manhattan predicts abnormally good performance not only for the

Table 2
The weather's power to predict anomaly strategy performance
The table reports results from the following OLS regressions:

$$\begin{aligned} R_t &= m + \varepsilon_t \\ R_t &= a + bX_{t-1} + \varepsilon_t \\ R_t &= a_H D_{H,t-1} + a_L D_{L,t-1} + \varepsilon_t \end{aligned}$$

where R is the monthly excess returns to an anomaly strategy, X is the predictive variable, the highest temperature recorded at the Central Park Weather station over the month, and D_H and D_L are high and low dummies for the predictive variable (above and below the sample median, respectively). Specifically, the table reports estimated average monthly anomaly excess returns ($\hat{m}$), the sensitivity of anomaly returns to the preceding month's high temperature ($\hat{b}$), and the average excess returns to the strategies after hot and cold months ($\hat{a}_H$ and $\hat{a}_L$, respectively). The sample covers July 1973 through December 2012, and is determined by the availability of the quarterly data used in the construction of many of the strategies.

Strategy	$\hat{m}$	$\hat{b}$	$\hat{a}_H$	$\hat{a}_L$
Panel A: Strategies that perform significantly better after cold weather				
Market	0.47	-0.03	-0.02	0.89
	[2.60]	[-1.98]	[-0.08]	[3.64]
Size	0.28	-0.06	-0.60	1.05
	[1.48]	[-4.54]	[-2.18]	[4.10]
Value	0.44	-0.03	-0.04	0.85
	[2.81]	[-3.01]	[-0.16]	[4.03]
Long Run Reversals	0.52	-0.07	-0.41	1.33
	[2.78]	[-5.25]	[-1.54]	[5.31]
Asset Growth	0.47	-0.03	0.06	0.82
	[3.14]	[-3.01]	[0.28]	[4.06]
Asset Turnover	0.47	-0.02	0.20	0.70
	[3.05]	[-2.16]	[0.90]	[3.34]
Panel B: Strategies that perform significantly better after hot weather				
Return-on-assets	0.77	0.06	1.62	-0.05
	[3.45]	[3.75]	[5.14]	[-0.15]
Earnings-to-price	1.07	0.04	1.55	0.61
	[5.03]	[2.57]	[5.12]	[2.05]
Gross Margins	-0.02	0.03	0.59	-0.56
	[-0.17]	[3.66]	[3.12]	[-3.16]
Piotroski's F-score	0.39	0.05	1.09	-0.22
	[2.14]	[3.65]	[4.14]	[-0.91]
Earnings Momentum (PEAD)	0.74	0.03	1.18	0.32
	[4.52]	[2.87]	[5.07]	[1.40]
Failure Probability	0.96	0.10	2.24	-0.29
	[2.83]	[4.14]	[4.71]	[-0.62]
Ohlson's O-score	0.39	0.06	1.28	-0.46
	[1.97]	[4.33]	[4.58]	[-1.69]
Idiosyncratic Volatility	0.36	0.06	1.31	-0.54
	[1.21]	[2.66]	[3.06]	[-1.29]

market, but also for small cap strategies, value strategies, and strategies based on long run reversals, asset growth, and asset turnover. Hot weather has significant power predicting abnormally good performance for many earnings related anomalies, including those based on return-on-assets, earnings-to-price, gross margins, Piotroski's (2000) F-score measure of financial strength, and earnings momentum, as well as those based on Ang et. al.'s (2006) idiosyncratic volatility puzzle and the default measures of Campbell et. al. (2008) and Ohlson (1980).

2.3. Other climatic predictors

The preceding section suggests that the weather has a material impact on the behavior of traders. The direct mechanism, whereby local weather impacts traders' moods, is more difficult to establish, however, as untabultated results show the weather in Bozeman, Montana, or Hawaii, has about as much power predicting anomaly performance as the weather in New York City. A critic may thus say that the weather is not important per se, but just picks up on strong seasonal components in the anomalies' performances—indeed, it is well know that the size effect is concentrated in January, a cold month (Keim 1983, Reinganum 1983).

This section addresses these concerns by showing that non-seasonal climatic variables, the global temperature anomaly ("global warming") and the quasiperiodic Pacific temperature anomaly ("El Niño"), also have significant power predicting anomaly performance. Bansal and Ochoa (2012) show that one of these variables, global warming, has power predicting cross-country differences in equity returns, concluding that "increases in global temperature have a negative impact on economic growth in countries closer to the Equator," so that "countries closer to the Equator carry a positive temperature risk premium." I show here that these variables predict the performance of several anomalies over time.

Figure 3 provides the evolution of these variables. Panel A shows monthly global average land temperature relative to the 1951-1980 base period. Panel B shows monthly deviations of the Pacific Ocean surface temperature, measured between 0°-10° South and 90°-

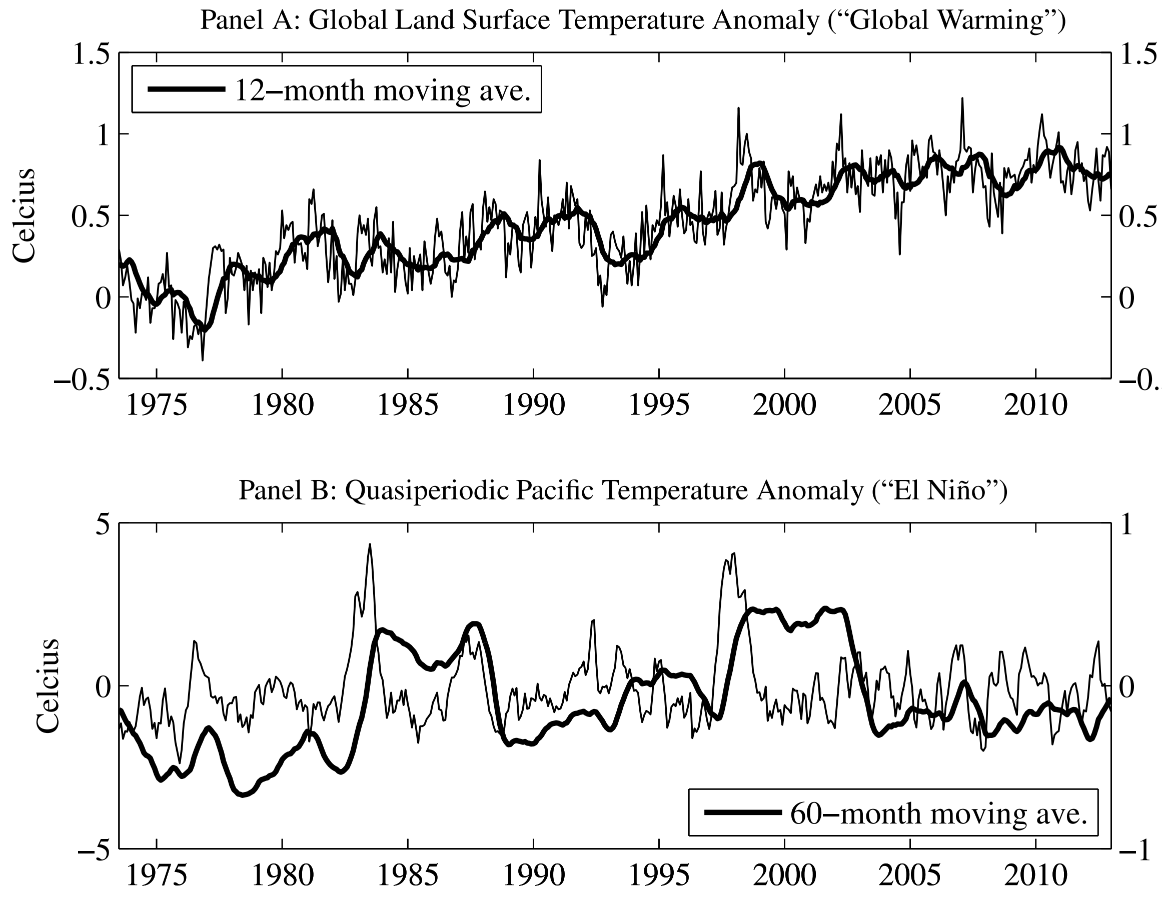

Fig. 3. Other Climatic Variables. This figure shows the levels of two non-seasonal climatic variables. Panel A shows the global average land temperature relative to the 1951-1980 base period. Panel B shows the deviations from average surface temperatures of the tropical Eastern Pacific Ocean. The data cover July 1973 to December 2012.

80° West, from the average measured over a 1971-2000 base period. The global temperature anomaly data come from National Aeronautics and Space Administration’s (NASA) Goddard Institute for Space Studies and are available at http://data.giss.nasa.gov/gistemp/, while the El Niño data come from the National Oceanic and Atmospheric Administration (NOAA) and are available at http://www.cpc.ncep.noaa.gov/data/indices/.

Table 3 shows the power these variables have predicting anomaly performance. Panel A shows that global warming is bad for value strategies and long run reversal strategies, but good for strategies based on market power (gross margins). A 12-month moving average

Table 3
Climatic variables' power to predict anomaly strategy performance

The table reports results from the following OLS regressions:

$$
\begin{aligned}
R_t &= m + \varepsilon_t \\
R_t &= a + bX_{t-1} + \varepsilon_t \\
R_t &= a_H D_{H,t-1} + a_L D_{L,t-1} + \varepsilon_t
\end{aligned}
$$

where R is the monthly excess returns to an anomaly strategy, X is the predictive variable (the global temperature anomaly [global warming], or the quasiperiodic Pacific temperature anomaly [El Niño]), and D_H and D_L are high and low dummies for the predictive variable (above and below the sample median, respectively). Specifically, the table reports estimated average monthly anomaly excess returns ($\hat{m}$), the sensitivity of anomaly returns to the predictive variable ($\hat{b}$), and the average excess returns to the strategies after high and low months ($\hat{a}_H$ and $\hat{a}_L$, respectively). The sample covers July 1973 through December 2012, and is determined by the availability of the quarterly data used in the construction of many of the strategies.

Strategy	$\hat{m}$	$\hat{b}$	$\hat{a}_H$	$\hat{a}_L$
Panel A1: Global Temperature Anomaly as predictive variable				
Value	0.50	-1.79	0.11	0.88
	[2.73]	[-2.99]	[0.42]	[3.44]
Long Run Reversals	0.46	-1.59	0.13	0.79
	[2.07]	[-2.15]	[0.42]	[2.50]
Gross Margins	0.00	0.97	0.25	-0.25
	[-0.01]	[1.97]	[1.19]	[-1.19]
Panel A2: Global Temperature Anomaly 12-month moving average as predictive variable				
Earnings-to-price	1.11	-2.24	0.75	1.47
	[5.10]	[-2.18]	[2.44]	[4.78]
Investment	0.61	-1.68	0.32	0.89
	[3.91]	[-2.32]	[1.45]	[4.09]
Panel B1: El Niño as predictive variable				
Accruals	0.26	0.30	0.53	0.00
	[1.87]	[2.29]	[2.64]	[0.02]
Beta Arbitrage	0.56	0.43	1.14	-0.01
	[2.82]	[2.31]	[4.06]	[-0.03]
Panel B2: El Niño 60-month moving average as predictive variable				
Gross Profitability	0.34	1.36	0.61	0.07
	[2.10]	[2.52]	[2.67]	[0.31]
Gross Margins	0.00	1.33	0.31	-0.31
	[-0.01]	[2.69]	[1.47]	[-1.48]
Piotroski's F-score	0.47	1.54	0.69	0.25
	[2.06]	[2.05]	[2.14]	[0.78]
Failure Probability	0.87	2.78	1.33	0.41
	[2.53]	[2.43]	[2.74]	[0.84]
Ohlson's O-score	0.30	2.03	0.69	-0.10
	[1.45]	[3.01]	[2.42]	[-0.36]
Net Issuance	0.73	1.83	1.09	0.36
	[5.43]	[4.15]	[5.81]	[1.93]
Idiosyncratic Volatility	0.33	2.29	0.68	-0.02
	[0.96]	[1.98]	[1.39]	[-0.03]
Industry Momentum	0.70	-2.16	0.23	1.17
	[2.49]	[-2.32]	[0.58]	[2.95]

of the global temperature anomaly, which takes out its seasonal component, also predicts poor stock performance for firms that invest a lot or have high earnings-to-price ratios.

Panel B shows that warm ocean temperatures in the East Pacific are a significant predictor of good performance for Sloan's (1999) accrual based strategy. In fact all of the returns to the strategies based on "earnings quality" come in the months when the East Pacific is unusually warm. Similarly, all the returns to a beta arbitrage strategy, which buys low market beta stocks, shorts high market beta stocks, and hedges the residual beta with a long market position, come at the peaks of the El Niño. A 60-month moving average, which smoothes temperatures over the basic five year periodicity of the phenomena, and thus measures the amplitude of the preceding El Niño, as opposed to where we are in the current one, predicts strong performance for the strategies based on gross profitability, net stock issuance, and the failure and default probability measures of Campbell et. al. (2008) and Ohlson (1980), as well as strategies based on market power, Piotroski's F-score, and idiosyncratic volatility. It predicts poor performance for the one month industry momentum of Moskowitz and Grinblatt (1999).

2.4. Celestial predictors of anomaly performance

Since ancient times man has looked to the sky to guide economic activity. Modern investors, even those sceptical of the heavens' direct influence on the human world, should recognize the potential for celestial phenomena to impact market prices at least indirectly, through the trading behavior of less sceptical investors. Dichev and Janes (2003) and Yu, Zheng, and Zhu (2006) show the importance of the skies for modern markets, documenting the influence of the lunar phase on equity returns. Yu, Zheng, and Zhu ground their work on theory, writing that "...since psychological studies associate full moon phases with depressed mood, this study hypothesizes that stocks are valued less and thus returns are lower during full moon periods." Their empirical tests support this hypothesis, despite Kamstra, Kramer and Levi's (2003) work showing that investor depression raises expected returns.

I show here that other celestial phenomena, related to both the planets and stars, are also powerful predictors of asset prices. Both the planetary aspects (i.e., the apparent proximity of two planets in the heavens to an earth observer) and sunspot activity have significant power predicting anomalies' returns.

The aspects of Mercury and Venus with the outer planets appear particularly important for the performance of anomalies, predicting the returns of the market, and strategies based on market cap, book-to-market, momentum, gross profitability, return-on-assets, market power, earnings surprises, Piotroski's F-score, failure probability, default probability, idiosyncratic volatility, asset growth, betting against beta, and both short and long run reversals. The aspects of the inner planets with the outer planets have periodicities of roughly a year, however, making it difficult to distinguish if these variables have power in their own right, or if their power simply derives from their correlation with the weather.[4] I consequently focus on the aspects of Saturn, and in particular its celestial relations to Mars and Jupiter. Indeed, the importance of Mars for equity markets has been known for some time. Its particular importance is not surprising, as Mars disproportionately influences our animal instincts, especially aggression, which is strongly associated with risk-taking. Rieder (1972) links retrograde stations of Mars (i.e., times when the progression of Mars through the heavens appears to reverse) to market collapses, while Meridian (1985) identifies a strong influence of the aspect of Mars with the asteroid Vesta on market cycles. This latter result may help explain another well known anomaly, the Presidential stock market cycle, i.e., the fact that market returns are significantly higher in the last two years of a presidential cycle than they are in the first two. This fact, distinct from the market's superior performance under democrats discussed in Section 2.1, was first identified by Hirsch (1968) and formally tested by Allvine and O'Neill (1980). The Mars-Vesta cycle has a basic periodicity of 3.90 years, similar to the time between elections. "Early" and "late" dummies for the presidential cycle may therefore simply proxy for whether Mars and Vesta are in conjunction or opposed.

The aspects of Saturn with Mars and Jupiter are shown in Panels A and B of Figure

[4] A proper analysis would of course need to consider the possibility that the weather predicts anomaly performance simply because it proxies for the conjunctions of Mercury and Venus with the outer planets.

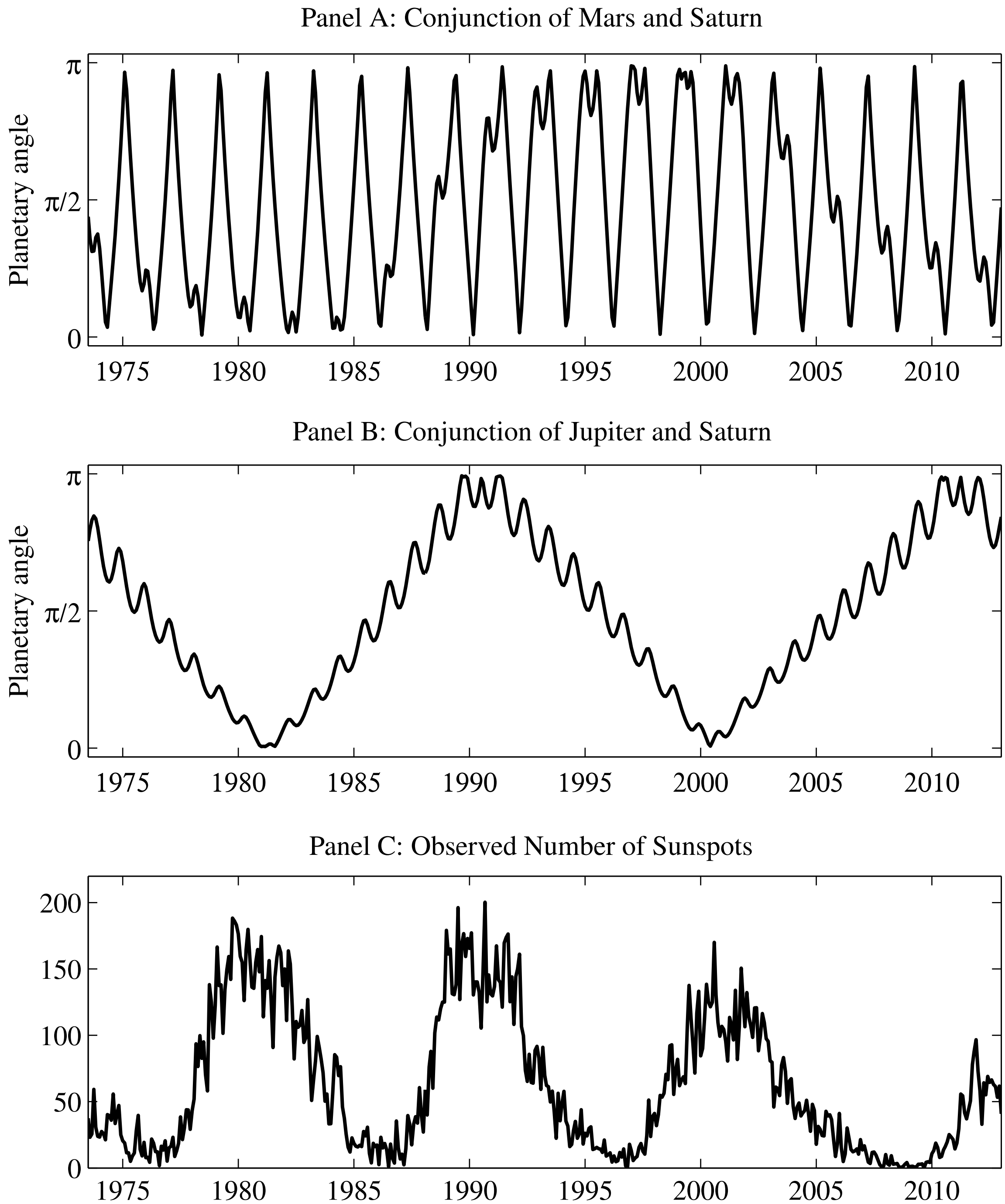

Fig. 4. Celestial phenomena. This figure shows the levels of the celestial predictive variables. Panel A shows the aspect of Mars and Saturn (i.e., the angle between the planets to an earth observer). Panel B shows the aspect of Jupiter and Saturn. Panel C shows the number of sunspots observed each month. The data cover July 1973 to December 2012.

4, respectively. The synodic period (i.e., the major periodicity of an aspect) is determined by the product of the orbital periods of the two outer planets in the triangle (two extra-terrestrial planets and earth), divided by the difference in these orbital periods. The orbital periods of Mars, Jupiter and Saturn are 1.881, 11.86 and 29.46 years, implying major periodicities of the conjunction of Saturn with Mars and Jupiter of just over two years and just under 20 years, respectively. Planetary aspects are derived from the Keplerian equations, available from NASA's Jet Propulsion Laboratory at http://ssd.jpl.nasa.gov/?planet_pos.

Panel C of Figure 4 shows the level of sunspot activity, a variable I include because of previous work showing its link to economic activity. Modis (2007) establishes a correlation between sunspots, gross domestic product, and the Dow Jones Industrial average (see also Plosser and Schwert, 1978). Most impressively, Modis (2007) predicts, solely on the basis of expected solar activity, a market peak in June, 2008, the exact month in which a bear market was official declared for U.S. equities, as the Dow had fallen 20% from its high. The periodicity of the solar cycle is roughly ten and a half years. Sunspot data are compiled by the Solar Influences Data Analysis Center, and available at http://solarscience.msfc.nasa.gov/greenwch/spot_num.txt.

Table 4 presents results of predictive regressions employing these celestial predictors. Panel A shows that the aspect of Mars and Saturn is a powerful predictor of the anomaly performance. The market performs significantly better when Mars and Saturn are opposed. Times when Mars and Saturn are struggling for dominance and their energies are polarized appear to be particularly propitious times to invest in the market. In contrast, high quality firms' outperformance of lower quality firms appears to occur primarily when Mars and Saturns' energies are strongly blended. Many earnings related anomalies, including those based on return-on-assets, earnings-to-price, idiosyncratic volatility, and the distress measures of Ohlson (1980) and Campbell et. al. (2008), perform better when these planets are in conjunction, appearing in close proximity to an earth observer.

Panel B shows that strategies based on market cap, net stock issuance, and asset growth, as well as Frazzini and Pedersen's (2013) betting-against-beta (BAB) strategy, perform

Table 4
Celestial phenomena and anomaly strategy performance

The table reports results from the following OLS regressions:

$$\begin{aligned} R_t &= m + \varepsilon_t \\ R_t &= a + bX_{t-1} + \varepsilon_t \\ R_t &= a_H D_{H,t-1} + a_L D_{L,t-1} + \varepsilon_t \end{aligned}$$

where R is the monthly excess returns to an anomaly strategy, X is the predictive variable (the aspect of Saturn with Mars or Jupiter, or the observed number of sunspots), and D_H and D_L are high and low dummies for the predictive variable (above and below the sample median, respectively). Specifically, the table reports estimated average monthly anomaly excess returns ($\hat{m}$), the sensitivity of anomaly returns to the predictive variable ($\hat{b}$), and the average excess returns to the strategies after high and low months ($\hat{a}_H$ and $\hat{a}_L$, respectively). The sample covers July 1973 through December 2012, and is determined by the availability of the quarterly data used in the construction of many of the strategies. Frazzini and Pedersen's (2013) betting-against-beta (BAB) is only available through March 2012.

Strategy	$\hat{m}$	$\hat{b}$	$\hat{a}_H$	$\hat{a}_L$
Panel A: Angle between Mars and Saturn as predictive variable				
Market	0.51	0.53	0.98	0.04
	[2.37]	[2.29]	[3.22]	[0.15]
Return-on-assets	0.69	-0.52	0.14	1.24
	[3.07]	[-2.17]	[0.45]	[3.91]
Earnings-to-price	1.11	-0.55	0.49	1.74
	[5.10]	[-2.37]	[1.60]	[5.66]
Failure Probability	0.87	-0.76	0.09	1.65
	[2.53]	[-2.06]	[0.19]	[3.39]
Ohlson's O-score	0.30	-0.52	-0.07	0.67
	[1.45]	[-2.38]	[-0.26]	[2.32]
Idiosyncratic Volatility	0.33	-0.85	-0.50	1.16
	[0.96]	[-2.28]	[-1.01]	[2.38]
Panel B: Angle between Jupiter and Saturn as predictive variable				
Size	0.24	-0.55	-0.19	0.66
	[1.12]	[-2.34]	[-0.63]	[2.22]
Net Issuance	0.73	-0.45	0.41	1.05
	[5.43]	[-3.05]	[2.16]	[5.57]
Asset Growth	0.57	-0.48	0.17	0.97
	[3.25]	[-2.48]	[0.69]	[3.92]
BAB	0.97	-0.39	0.44	1.47
	[6.03]	[-2.18]	[1.95]	[6.62]
Panel C1: Observed number of sunspots as predictive variable				
UMD	0.66	0.01	0.99	0.32
	[3.14]	[2.25]	[3.36]	[1.08]
Earnings Momentum (PEAD)	0.70	0.01	0.96	0.44
	[4.27]	[2.18]	[4.14]	[1.91]
Panel C2: Cyclic moving average of observed number of sunspots as predictive variable				
Size	0.24	-0.04	-0.48	0.95
	[1.12]	[-2.09]	[-1.61]	[3.22]
Ohlson's O-score	0.30	0.05	1.04	-0.45
	[1.45]	[3.11]	[3.67]	[-1.59]
Seasonality	0.87	0.04	1.06	0.68
	[4.56]	[2.70]	[3.94]	[2.50]

significantly better when Jupiter and Saturn are in conjunction. These data suggest that polarization of Jupiter and Saturn, which occurs when these planets are in opposition, may portend difficulties with growth, and should perhaps be taken as a sign to delay plans for rapid expansion.[5]

Panel C shows that sunspots are a significant predictor of the performance of strategies based on both price and earnings momentum. High levels of solar activity seem to inhibit investors' capacity to process information, reducing the rate at which news gets incorporated into prices. This increases the profitability of strategies that exploit slow adjustments of prices to fundamentals. Strategies that trade on prior year's stock performance and earnings surprises consequently have returns that are significantly positively correlated with the number of sunspots observed in the previous month.

The total number of sunspots observed over the preceding solar cycle (125-months) also has significant power predicting anomaly performance. This number, which measures the amplitude of the last solar cycle, as opposed to where one is in the current cycle, predicts the performance of strategies based on market capitalization, Ohlson's O-score, and Heston and Sadka's (2008) seasonality in stocks' performances. Unusually intense solar cycles seem to predict poor future performance for small caps, but strong future performance for strategies that bet on stocks that performed well in the same calendar month in preceding years, or against high default probability stocks.

On a historical note, sunspot activity also appears to have played a significant role in some of the most famous market distortions of all time. Consistent with the observed coincidence between high levels of sunspot activity, investors' difficulties processing information, and underreaction, low levels of sunspot activity appear strongly related to overreaction. The Dutch Tulip mania, which peaked in 1637, occurred at a time when sunspot activity was collapsing, near the start of the Maunder Minimum, a period during which

[5] The aspect of Jupiter and Saturn also appear to influence investor sentiment, explaining more than ten percent of the variation in the Baker-Wurgler Index. This seems largely unrelated to the power that either series has predicting anomaly performance, however, as regressions employing both variables in all cases yield slope estimates that are similar to their univariate estimates.

sunspot activity almost ceased.[6] The collapse of the South Sea Bubble, which peaked in 1720, coincides almost exactly with the Maunder Minimum's end. More recently, both Black Monday (October, 1987) and the start of the great recession (2007) came at minimums in the solar cycle, times of negligible sunspot activity. A more rigorous study of the relation between sunspots and bubbles may present an interesting avenue for further research, with potentially significant implications for policy makers and monetary authorities.

3. Conclusion

This paper documents that several interesting variables appear to have power predicting the performance of some of the best known anomalies. Standard predictive regressions fail to reject the hypothesis that the party of the U.S. President, the weather in Manhattan, global warming, El Niño, sunspots, or the conjunctions of the planets, are significantly related to anomaly performance. These results are striking, and quite surprising. In fact, some readers may be inclined to reject some of this paper's conclusions solely on the grounds of plausibility. I urge readers to consider this option carefully, however, as doing do so entails rejecting the standard methodology on which the return predictability literature is built.[7]

Instead, the success of the tests performed here could encourage further research. It seems likely that others could replicate my success, especially given the proliferation of anomalies, the exponential growth in easily obtainable, machine readable data on candidate explanatory variables, and the ease of running these sorts of regressions.[8] Potential investigators should think carefully about this line of work.

[6] This period was also coincident with the "little ice age" during which the winters in Europe and America were unusually cold.

[7] If one insists on rejecting the conclusion that El Ninõ, solar activity, and the planetary aspects have significant power predicting anomaly performance, when standard predictive regressions fail to reject the hypotheses that these variables are unrelated to anomaly returns, than one must reject some other precept of the methodology. I suppose that one could, instead, question the assumption, completely standard in the literature, of a time homogeneous linear relation between expected returns and the predictive variable. For a discussion of some related issues, see Roll (1977).

[8] Ferson, Sarkissian and Simin (2003, 2008) discuss some associated issues, especially when the predictive variables are persistent, like many of those considered in this study.

A. The anomalies

All strategies are long/short deciles (NYSE breakpoints) from a sort on the given signal. Returns are value-weighted. The third column gives the rebalance frequency. Detailed construction details and return series are provided at http://rnm.simon.rochester.edu/data_lib/index.html.

Anomaly	Sorting variable	Rebal.	Reference(s)
Size	Market equity	Annual	Banz (1981)
Value	Book-to-market equity	Annual	Rosenberg, Reid, Lanstein (1985), Fama and French (1993)
Momentum	Prior year's stock performance excluding the most recent month	Monthly	Jegadeesh and Titman (1994)
Gross profitability	Gross profits-to-assets	Annual	Novy-Marx (2013)
PEAD	Standardized Unexpected Earnings (SUE)	Monthly	Foster, Olsen, and Shevlin (1984)
Long run reversals	Prior five year's stock performance excluding the most recent year	Monthly	De Bondt and Thaler (1987)
Net issuance	Net stock issuance	Monthly	Pontiff and Woodgate (2008), Fama and French (2008)
Earnings quality	Accruals	Annual	Sloan (1996)
Asset growth	Change in totla assets	Annual	Titman, Wei, and Xie (2004)
Investment	Change in property, plant and equipment, and inventories	Annual	Lyandres, Sun, and Zhang (2008)
Piotroski's F-score	Piotroski's F-score	Annual	Piotroski (2000)
Earnings-to-price	Earnings before extraordinary items (IBQ) scaled by market capitalization	Monthly	Chen, Novy-Marx, and Zhang (2010)
Return on assets	Earnings before extraordinary items scaled by assets	Monthly	Chen, Novy-Marx, and Zhang (2010)
Asset turnover	Sales-to-assets	Annual	Novy-Marx (2013)
Gross margins	Gross profits-to-sales	Annual	Novy-Marx (2013)
Ohlson's O-score	Estimated default probability	Monthly	Ohlson (1980)
Failure probability	Estimated failure probability	Monthly	Campbell, Hilscher, and Szilagyi (2008)
Idiosyncratic volatility	Standard deviation of residuals from regressions of past three months' daily returns on daily Fama-French factors	Monthly	Ang, Hodrick, Xing, and Zhang (2006)
Industry momentum	Prior month's industry return	Monthly	Moskowitz and Grinblatt (1999)
Seasonality	Average return in the coming calendar month over the preceding five years	Monthly	Heston and Sadka (2008)
Beta arbitrage	Estimated market beta	Monthly	Black (1972), Frazzini and Pedersen (2013)

References

[1] Allvine, F.C., O'Neill, D.E., 1980. Stock market returns and the presidential election cycle: implications for market efficiency. Financial Analysts Journal 36, 49-56.

[2] Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

[3] Baker, M., Wurgler, J., 2000. The equity share in new issues and aggregate stock returns. Journal of Finance 55, 2219–2257.

[4] Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 55, 1645–1680.

[5] Bansal, R., Ochoa, M., 2012. Temperature, aggregate risk, and expected returns. NBER Working Paper No. 17575.

[6] Banz, R.W., 2012. The relationship between return and market value of common stocks. Journal of Financial Economics 9, 3–18.

[7] Barro, R.J., 1989. An efficiency-wage theory of the weather. Journal of Political Economy 97, 999–1001.

[8] Black, F., 1972. Capital market equilibrium with restricted borrowing. Journal of Business 45, 444–455.

[9] Campbell, J.Y., Stock returns and the term structure. Journal of Financial Economics 18, 373–400.

[10] Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. Journal of Finance 63, 2899–2939.

[11] Chen, L., Novy-Marx, R., Zhang., L., 2010. An alternative three factor model. Working Paper.

[12] Cao, M., Wei, J., 2005. Stock market returns: a note on temperature anomaly. Journal of Banking & Finance 29, 1559–1573.

[13] Cooper, M.J., Gutierrez, R.C., Hameed, A., 2004. Market states and momentum. Journal of Finance 59, 1345–1365.

[14] De Bondt, W.F.M., Thaler, R.H., 1987. Further evidence on investor overreaction and stock market seasonality. Journal of Finance 42, 557–581.

[15] Dichev, I.D., Janes, T.D., 2004. Lunar cycle effects in stock returns. Journal of Private Equity 6, 8–29.

[16] Fama, E.F., French, K.R., 1988. Dividend yields and expected stock returns. Journal of Financial Economics 22, 3–25.

[17] Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

[18] Fama, E.F., French, K.R., 2008. Dissecting anomalies. Journal of Finance 63, 1653–1678.

[19] Fama, E.F., Schwert, G.W., 1977. Asset returns and inflation. Journal of Financial Economics 5, 115–146.

[20] Ferson, W., Sarkissian, S., Simin, T., 2003. Spurious regressions in financial economics. Journal of Finance 58, 1393–1413.

[21] Ferson, W., Sarkissian, S., Simin, T., 2008. Asset pricing models with conditional alphas and betas: the effects of data snooping and spurious regression. Journal of Financial and Quantitative Analysis 43, 331–354.

[22] Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. The Accounting Review 59, 574–603.

[23] Frazzini, A., Pedersen, L.H., 2013. Journal of Financial Economics forthcoming.

[24] French, K.R., Schwert, G.W., Stambaugh, R.F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.

[25] Heston, S.J., Sadka, R., 2008, Seasonality in the cross-section of stock returns. Journal of Financial Economics 87, 418–445.

[26] Hirsch, Y., 1968. Stock Trader's Almanac.

[27] Hirshleifer, D., Shumway, T., 2003. Good day sunshine: stock returns and the weather. Journal of Finance 63, 1009–1032.

[28] Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65–91.

[29] Kamstra, M.J., Kramer, L.A., Levi, M.D., 2003. Winter blues: a SAD stock market cycle. The American Economic Review 93, 324–343.

[30] Keim, D.B., 1983, Size-related anomalies and stock return seasonality: further empirical evidence. Journal of Financial Economics 12, 13–32.

[31] Keim, D.B., Stambaugh, R.F., 1986. Predicting returns in the stock and bond markets. Journal of Financial Economics 17, 357–390.

[32] Lamont, O.A., Stein, J.C., 2004. Aggregate short interest and market valuations. American Economic Review 94, 29–32.

[33] Lemmon M., Portniaquina, E., 2006. Consumer confidence and asset prices: some empirical evidence. Review of Financial Studies 19, 1499–1529.

[34] Lettau, M., Ludvigson, S., 2001. Consumption, aggregate wealth, and expected stock returns. Journal of Finance 56, 815–849.

[35] Mankiw, N.G., Weinzierl, M., 2010. The optimal taxation of height: a case study of utilitarian income redistribution. American Economic Journal: Economic Policy 2, 155–176.

[36] Meridian, B., 1985. The Mars Vesta cycle in U.S. stock prices. Journal of the Astrological Association of Great Britain 25, 121.

[37] Merton, R.C., 1980. On Estimating the expected return to the market: an exploratory investigation. Journal of Financial Economics 8, 323–361.

[38] Moskowitz, T.J., Grinblatt, M., 1999. Do industries explain momentum? Journal of Finance 54, 1249–1290.

[39] Modis, T., 2007. Sunspots, GDP and the stock market. Technological Forecasting & Social Change 74, 1508–1514.

[40] Novy-Marx, R., 2013, The other side of value: the gross profitability premium. Journal of Financial Economics 108, 1–28.

[41] Novy-Marx, R., Velikov, M., 2013. Anomalies and their trading costs. Working paper.

[42] Ohlson, J.A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research 18, 109–131.

[43] Piotroski, J.D. 2000. Value investing: the use of historical financial statement information to separate winners from losers. Journal of Accounting Research 38, 1–41.

[44] Plosser, C.I., Schwert, G.W., 1978. Money, income and sunspots: measuring economic relationships and the effects of differencing. Journal of Monetary Economics 4, 637–660.

[45] Pontiff, J., Woodgate, A., 2008. Share issuance and the cross-section of returns. Journal of Finance 63, 921–945.

[46] Powell, J.G., Shi, J., Smith, T., Whaley, R.E., 2007. The persistent presidential dummy. Journal of Portfolio Management 33, 133–143.

[47] Reinganum, M.R. 1983, The anomalous stock market behavior of small firms in January: empirical tests for tax–loss selling effects. Journal of Financial Economics 12, 89–104.

[48] Rieder, T., 1972. Astrological warnings and the stock market, Pagurian Press, Toronto.

[49] Roll, R., 1977. A critique of the asset pricing theory's tests, part I: on past and potential testability of the theory. Journal of Financial Economics 4, 129–176.

[50] Rosenberg, B., Reid, K., Lanstein, R., 1985. Persuasive evidence of market inefficiency. Journal of Portfolio Management 11, 9–16.

[51] Santa-Clara, P., Valkanov, R., 2003. The presidential puzzle: political cycles and the stock market. Journal of Finance 58, 1841–1872.

[52] Sloan, R.G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71, 289–315.

[53] Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: investor sentiment and anomalies. Journal of Financial Economics 104, 288–302.

[54] Titman, S., Wei, K.C.J., Xie, F., 2004. Capital investments and stock returns. Journal of Financial and Quantitative Analysis 39, 677–700.

[55] Yuan, K., Zheng, L., Zhu, Q., 2006. Are investors moonstruck? Lunar phases and stock returns. Journal of Empirical Finance 13, 1–23.