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PSEUDO-PREDICTABILITY IN CONDITIONAL ASSET PRICING TESTS: EXPLAINING ANOMALY PERFORMANCE WITH POLITICS, THE WEATHER, GLOBAL WARMING, SUNSPOTS, AND THE STARS

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ABSTRACT

Ferson, Sarkissian and Simin (2003) warn that persistence in expected returns generates spurious regression bias in predictive regressions of stock returns, even though stock returns are themselves only weakly autocorrelated. Despite this fact a growing literature attempts to explain the performance of stock market anomalies with highly persistent investor sentiment. The data suggest, however, that the potential misspecification bias may be large. Predictive regressions of real returns on simulated regressors are too likely to reject the null of independence, and it is far too easy to find real variables that have "significant power" predicting returns. Standard OLS predictive regressions find that the party of the U.S. President, cold weather in Manhattan, global warming, the El Niño phenomenon, atmospheric pressure in the Arctic, the conjunctions of the planets, and sunspots, all have "significant power" predicting the performance of anomalies. These issues appear particularly acute for anomalies prominent in the sentiment literature, including those formed on the basis of size, distress, asset growth, investment, profitability, and idiosyncratic volatility.

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1 Introduction

Investor sentiment is increasingly used as a variable to predict the performance of trading strategies. Baker and Wurgler (2006), Lemmon and Portniaguina (2006), and Stambaugh, Yu, and Yuan (2012) find that investor sentiment has significant power predicting the performance of 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. These papers all test for a relation between the predictive variable (e.g., investor sentiment, or past market performance) and the expected returns to some trading strategy (e.g., value, or momentum), and strongly reject the null that the strategy's expected returns are independent of the predictive variable. They conclude that the predictive variable has significant power forecasting the the strategy's performance.

An alternative explanation is that the tests are simply misspecified. If a trading strategy's expected returns vary slowly over time, then OLS regressions confer spurious power explaining returns on any slow moving "predictive variable." Time variation in risk premia introduces auto correlation in the returns data, though this is largely obscured by the high variability of returns. Standard "predictive regressions," which purport to test for a relation between the performance of an anomaly and some explanatory variable, report more power than they actually have to reject the null of independence. Persistence in expected returns and the explanatory variable reduce the number of effective observations, and test statistics calculated ignoring this fact overstate the test's power.

Ferson, Sarkissian and Simin (2003) show that the spurious regression bias of Granger and Newbold (1974) can be severe when studying return predictability, despite the fact that returns are first differences in prices and exhibit little persistence.[1] Because returns exhibit little persistence, the finance literature often ignores the potential bias towards rejecting independence. Predictive regressions do not, however, test for a relation between the predictive variable and returns. They test for a relation between the predictive variable and the *expected* returns (a level), which may be far more persistent. Ferson, Sarkissian and Simin (2003) show in simulations that if returns are noisy realizations of an auto regressive expected returns process, then independent autoregressive "news" processes, which by construction contain absolutely no information about expected returns, frequently appear to have power in sample. Predictive regressions, which regress realized returns on the independent news process, are too likely to reject the hypothesis of independence. This spurious regression bias interacts with and intensifies the data mining concerns of Foster, Smith, and Whaley (1997). Mining is more likely to uncover spurious, persistent regressors, and the regressors used in the literature to predict stock market performance tend to be persistent, suggesting that the power of some of these regressors is spurious.[2]

Similar biases are observed when "predicting" the performance of real world anomalies with simulated regressors. Predictive regressions are biased toward rejecting the indepen-

[1] This problem is distinct from that solved by Stambaugh (1999). Stambaugh (1999) derives the small sample properties of the OLS estimators for well specified regressions of returns on a slow moving predictor.

[2] Prominent persistent regressors used to predict market returns include 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 market performance, while Lettau and Lugvigson (2001) and Lamont and Stein (2004) find similar results using the consumption-wealth-ratio and aggregate short interest.

dence of the performance of a wide variety of investment strategies and independently generated noise with a persistent component. As a result it is much too easy to find "powerful" conditioning variables in the real world. The party of the U.S. President, the weather in Manhattan (or pretty much anywhere), global warming, the El Niño phenomenon, atmospheric pressure in the Arctic, the conjunctions of the planets, and sunspots, all have "significant power" predicting the performance of well known anomalies. The strategies prominent in the sentiment literature, including those formed on the basis of size, distress, asset growth, investment, profitability, and idiosyncratic volatility, appear particularly susceptible to the "predictive power" of obviously independent regressors.

This is not to say that the economic explanations provided in earlier papers for the observed correlations between sentiment, or past market performance, and the performance of market anomalies are incorrect. Many of these papers provide additional evidence, by investigating deeper implications of the proposed relation, such as asymmetries between the power that the conditioning variable has to predict the performance of the long and short side of the investment strategy. But all the tests employed in these papers, including these additional tests, are likely misspecified, and thus overstate the power the tests have to reject the null hypothesis that the predictive variable investigated is actually unrelated to the performance of the strategies.

2 An Illustration

The potential biases that arise from misspecification can be seen most easily in simulations, like those considered in Ferson, Sarkissian and Simin (2003). If expected returns follow an AR(1), then predictive regressions of realized returns on AR(1) noise processes with similar mean reversion rates are too likely to reject the null of independence. Suppose that returns are noisy realizations of expected returns, and that the expected return (λ_t) and a "news" (x_t) follow independent AR(1) processes with the same persistence a_1,

$$\begin{aligned} x_i &= \theta_x + a_1 x_{i-1} + \sigma_x \chi_i^x \\ \lambda_i &= \theta_\lambda + a_1 \lambda_{i-1} + \sigma_\lambda \chi_i^\lambda \\ r_i &= \lambda_{i-1} + \sigma_r \chi_i^r \end{aligned}$$

where the χ_i^x, χ_i^λ and χ_i^r are independent standard normal variables for each i. The return process and the "news" process are, by construction, independent.

Regressions of returns on lagged news, however, are too likely to reject the hypothesis of independence. Figure 1 shows test statistics on the slope coefficient on the explanatory variable from misspecified predictive regressions of returns on the lagged "news" process,

$$r_i = \alpha + \beta x_{i-1} + \epsilon_i .$$

The figure shows the test statistics on the slope coefficient for a million simulations of forty years of monthly data. The monthly persistence on the AR(1) process is $a_1 = 0.985$ (a half-life to shocks to the expected return process of 3.82 years), slightly less than the monthly autocorrelation observed in the Baker-Wurgler Index, and the shocks to the average return and return processes have volatilities of 1% and 16%, respectively ($\sigma_\lambda = 0.01$ and $\sigma_\epsilon = 0.16$). These parameters yield an auto correlation of monthly returns similar to

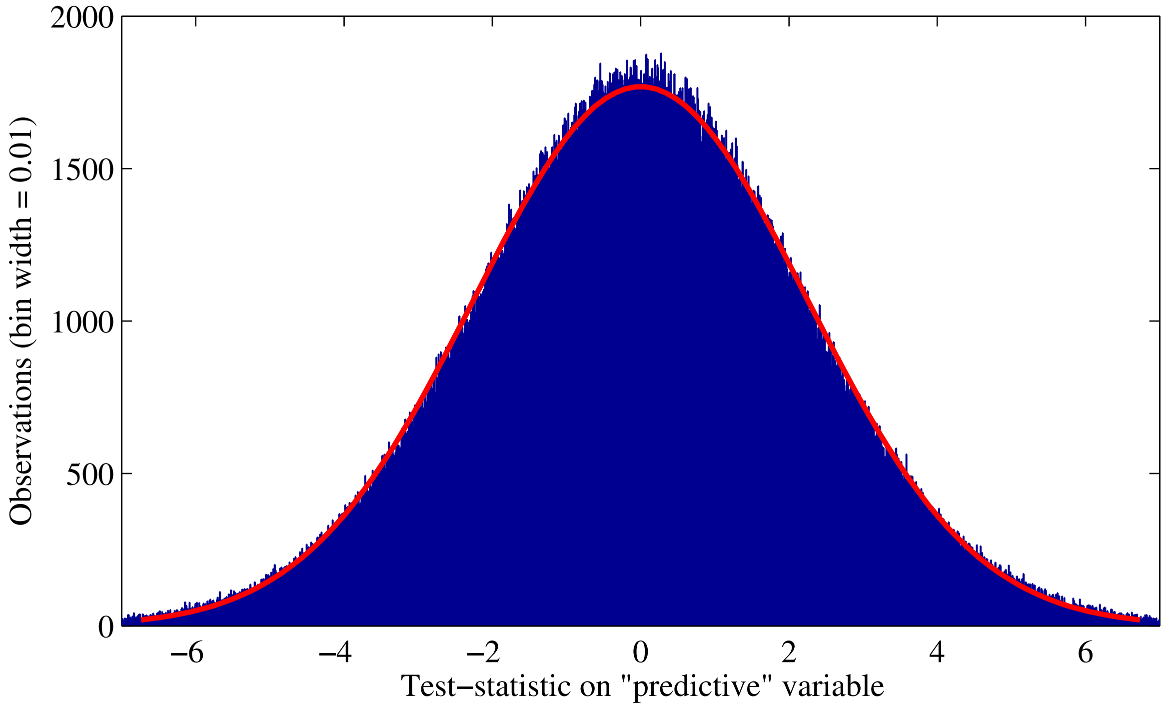

Figure 1. Distribution of test-statistic in simulated data
The figure shows results from predictive regressions of returns, which are noisy realizations of an AR(1) expected return process, onto independent AR(1) noise. The figure shows the number of realized slope coefficient test statistics in each 0.01 interval, estimated in a million sets of 40 year monthly series. Parameters used to generate the data are $a_1 = 0.985$ (a half-life to shocks to the average return process of 3.82 years), $\sigma_\lambda = 1\%$, and $\sigma_\epsilon = 16\%$, yielding an auto correlation of monthly returns of roughly 10%, similar to that observed in aggregate stock market data.

that observed in the aggregate stock market, roughly 10%. The figure shows the realized test statistics, in bins of width of 0.01. The distribution is basically normal with a SD of 2.29, implying the precision with which the slopes are estimated is overstated by more than a factor of two. The predictive regression is far too likely to reject the null that the "news" process is unrelated to returns, despite the fact that the two processes are independent by construction. The misspecified OLS regressions reject the hypothesis that returns are unrelated to AR(1) noise at the 5% level 39% of the time.

The standard deviation of test statistics in the misspecified regressions depends on the persistence of the shocks (i.e., the mean reversion speed of expected returns), and the relative magnitudes of the shocks to the expected return process and the returns process. More persistence in the expected return process, or a higher signal-to-noise ratio ($\sigma_\lambda/\sigma_\epsilon$), increase the autocorrelation in returns, magnifying the extent to which the precision of the slope coefficient in the predictive regression is over estimated. For example, if $\sigma_\lambda/\sigma_\epsilon = 0.25$, four times as high as that used in the simulations of Figure 1, then the standard deviation of the distribution of test statistics is more than twice as high, 5.73. With this parameterization the misspecified OLS regressions reject the hypothesis that returns are unrelated to AR(1) noise at the 5% level 73% of the time.

Figure 2 shows the standard deviation of the distribution of test statistics from predictive regressions like those employed to generate Figure 1, as a function of the monthly persistence in expected returns. The figure shows auto correlation coefficients of $a_1 \in [0.9, 0.995]$, implying half-lives of shocks to the expected return process of six months to 11.5 years, and depicts results for three different signal-to-noise ratios ($\sigma_\lambda/\sigma_\epsilon \in \{0.05, 0.1, 0.2\}$). Over the entire parameter space the misspecified tests are biased toward rejecting the null that the processes are unrelated, and this bias can be substantial. This conclusion is perhaps not surprising. The persistence in the expected return process introduces serial correlation in returns. This reduces the number of effective observations, and the predictive regressions, which treat the observations as independent, overstate the test's statistical power.

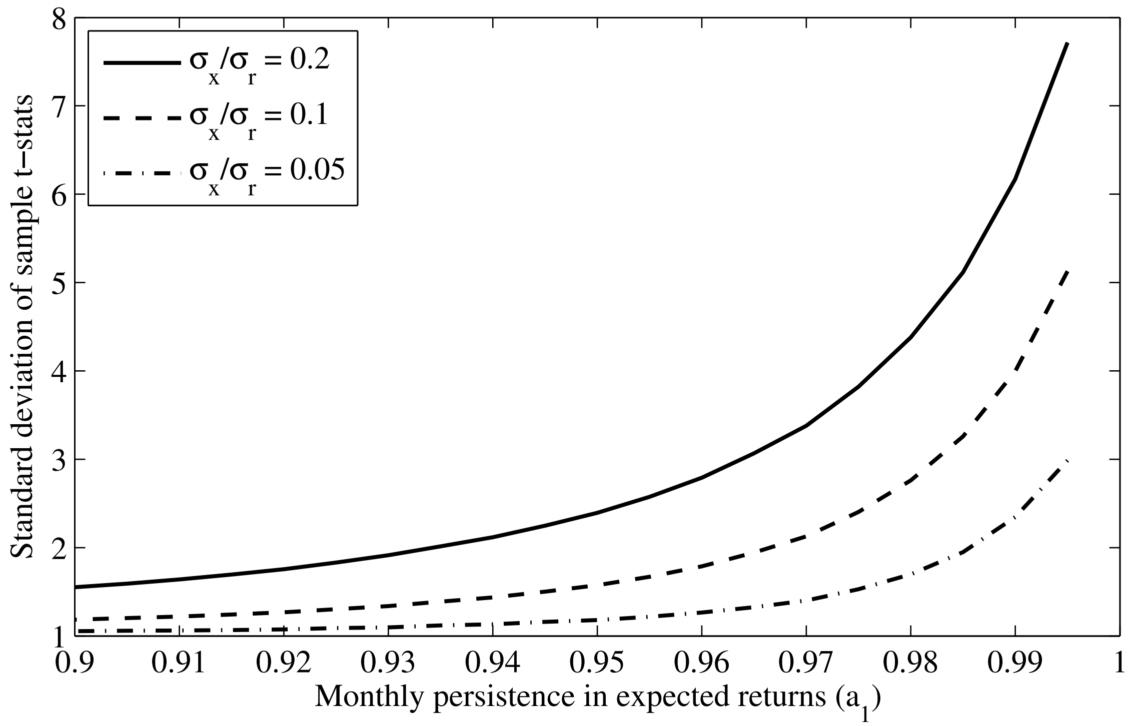

Figure 2. Standard deviation of test-statistic
The figure shows the standard deviation of test statistics from predictive regressions of simulated returns, which are noisy realizations of an AR(1) expected return process, onto independent AR(1) noise. The figure shows test statistic standard deviations for monthly expected return persistence between 0.9 and 0.995, implying half-lives of shocks to the expected return process of six months to 11.5 years, for three different signal-to-noise ratios ($\sigma_\lambda/\sigma_r \in \{0.05, 0.1, 0.2\}$).

3 Predicting real strategy performance with noise

Predictive regressions also tend to over-reject the null of independence for real anomaly returns. We can guarantee independence between anomaly strategy returns and a predictive variable by again simulating the predictive variable completely independently. Figure 3 shows results of regressions similar to those presented in the last section, which regress the returns to real market anomalies on simulated AR(1) noise. The dependent variables employed in the regressions are the returns to well known anomalies: a value strategy, an investment strategy, the asset growth strategy of Cooper, Gulen and Schill (2008), and the 12-month strategy of Heston and Sadka (2008). The strategies are constructed by sorting on book-to-market, investment (the change in property, plant and equipment plus the change in inventories)-to-assets, assets-to-lagged assets, and average stock performance in the same calendar month over the previous five years. All four strategies are long/short extreme deciles of a sort on the corresponding sorting variable, using NYSE breaks. Returns are value weighted. The value, investment, and asset growth portfolios are rebalanced at the end of July, while those based on seasonality are rebalanced monthly. The sample covers July 1973 to December 2010. The figure shows that predictive regressions are biased toward rejecting the hypothesis of independence for all four strategies.

These results are not specific to the AR(1) assumption on the predictive noise process. Figure 4 repeats the exercise using AR(2) noise as the predictive variable. Each predictive series is generated using

$$x_i = a_1 x_{i-1} + a_2 x_{i-2} + \epsilon_i,$$

where the coefficients a_1 and a_2 are chosen so that the autocorrelation coefficients are pseudo-periodic, and the ϵ_i are independent normally distributed shocks. I consider scenarios in which $a_2 \in (-1, -.9)$, implying a periodic (monthly) damping coefficient (i.e., persistence) of $\sqrt{-a_2} \in (0.95, 1)$, and an underlying sine wave frequency of either one or two years ($a_1 = \sqrt{-a_2}\cos(2\pi/N)$), where N is picked to be 12 or 24 months), though other choices yield similar results.

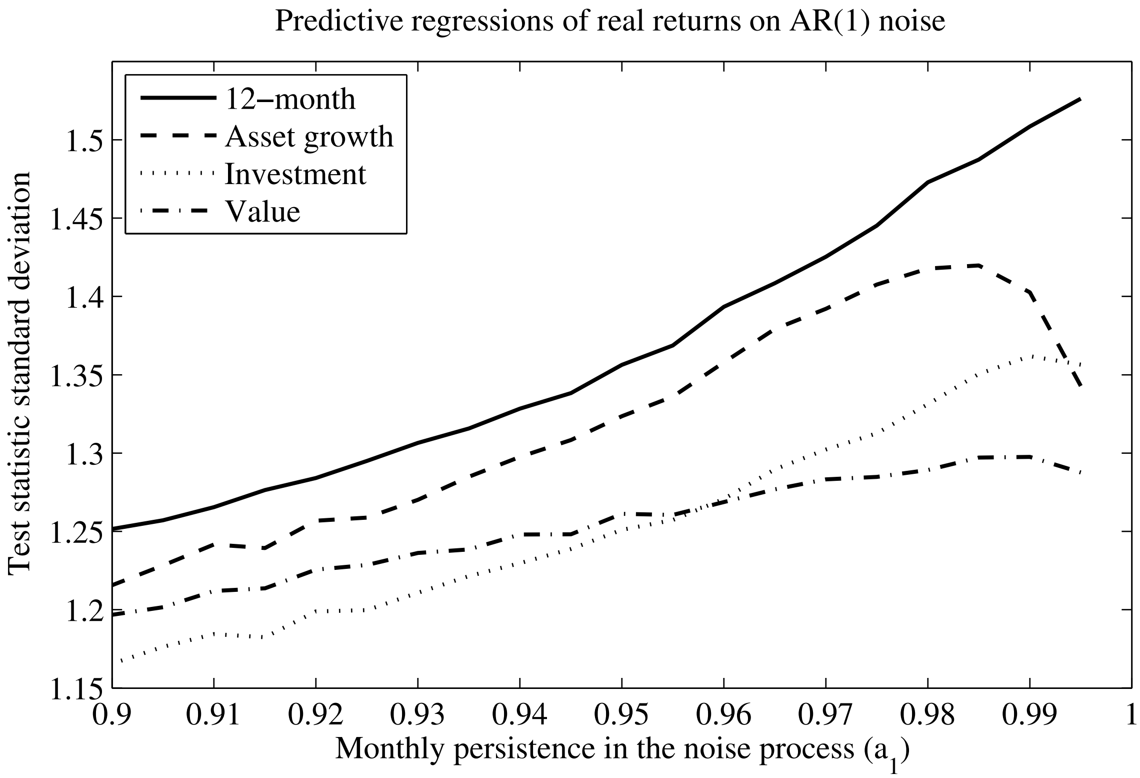

Figure 3. Standard deviation of test-statistics from regressions predicting anomaly performance with AR(1) noise.
The figure shows the standard deviation of test statistics from predictive regressions of the returns to strategies sorted on book-to-market, investment-to-assets, asset growth, and average stock performance in the same calendar month over the previous five years, onto independent AR(1) noise. The figure shows test statistic standard deviations for monthly persistence in the auto regressive noise process of $a_1 \in [0.9, 0.995]$, implying half-lives to shocks of six months to 11.5 years. Each standard deviation is estimated from 100,000 noise series. The sample covers July 1973 to December 2010.

The top panel shows results predicting the performance of real investment strategies based on size, long run past performance, and two distress strategies, using an AR(2) noise with a periodicity of one year. These strategies are constructed by sorting on size (end of year market capitalization), stock performance from three to one years prior, the failure probability measure of Campbell, Hilscher, and Szilagyi (2008), and the default risk

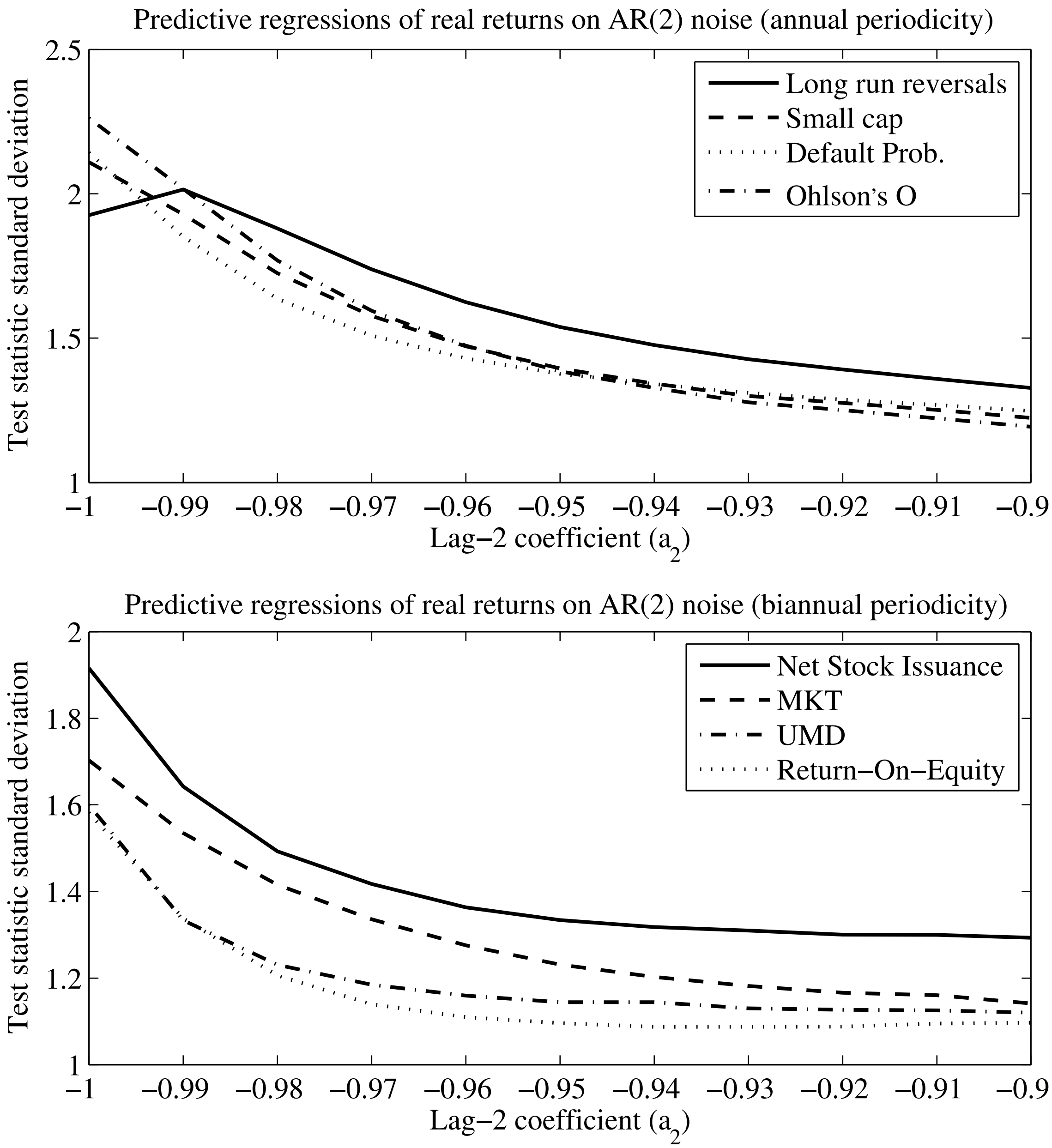

Figure 4. Standard deviation of test-statistics from regressions predicting anomaly performance with AR(2) noise.
The figure shows the standard deviation of test statistics from predictive regressions of 1) the returns to strategies sorted on size, long run past performance, and the distress measures of Campbell et. al (2008) and Ohlson (1980), onto independent AR(2) noise with an annual periodicity, and 2) the returns to the Fama-French market and momentum factors (MTK and UMD) and strategies sorted on net stock issuance and return-on-equity, onto independent AR(2) noise with a biannual periodicity. The figure shows test statistic standard deviations for $a_2 \in (-1, -0.95)$. Each test-statistic standard distribution is estimated from 100,000 noise series. The sample covers July 1973 to December 2010.

"O-score" of Ohlson (1980). These strategies are again long/short extreme value weighted deciles of a sort on the corresponding sorting variable, using NYSE breaks. The size portfolios are rebalanced at the end of July, while the strategies based on long run past performance, failure probability, and Ohlson's O-score are rebalanced monthly. The sample covers July 1973 to December 2010. Again, predictive regressions are too likely to reject the hypothesis of independence.

The bottom panel shows similar results for the returns to the market, UMD (the "up-minus-down" momentum factor maintained by Ken French), and strategies based on net stock issuance and return-on-equity (ROE), employing AR(2) noise with a periodicity of two years as the predictive variables. The ROE and issuance strategies are constructed by sorting on income before extraordinary items divided by market equity, and net stock issuance to market equity, respectively, and are again long/short extreme value weighted deciles sorted using NYSE breaks. The issuance portfolios are rebalanced at the end of July, while the ROE strategy is rebalanced monthly. The sample covers July 1973 to December 2010. The predictive regressions again overstate the power they have to reject the hypothesis of independence.

4 Spurious correlations in the data

This section takes the exercise one step further, predicting the returns to real strategies using real "predictive" variables. The results suggest that it is far too easy to find variables that have "significant power" in standard OLS predictive regressions. The party of the sitting U.S. President, cold weather in Manhattan, global warming, the El Niño phenomenon, atmospheric pressure in the Arctic, the conjunctions of the planets, and sunspots, all have "significant power" predicting the performance of a wide array of well known anomalies.

4.1 Predicting anomaly performance with political parties

Figure 5 shows the "predictive" variables used in the first set of regressions, a dummy for whether the sitting U.S. President is a Democrat. The sample covers January 1961 (Kennedy's inauguration) to December 2010.

Table 1 shows that since Kennedy took the presidency on January 20, 1961, essentially all of the equity premium, as well as all of the small cap stocks' outperformance of large caps, can be "explained" by the party of the sitting president. Over these 50 years the market has only outperformed T-Bills by an insignificant ten basis points per month in

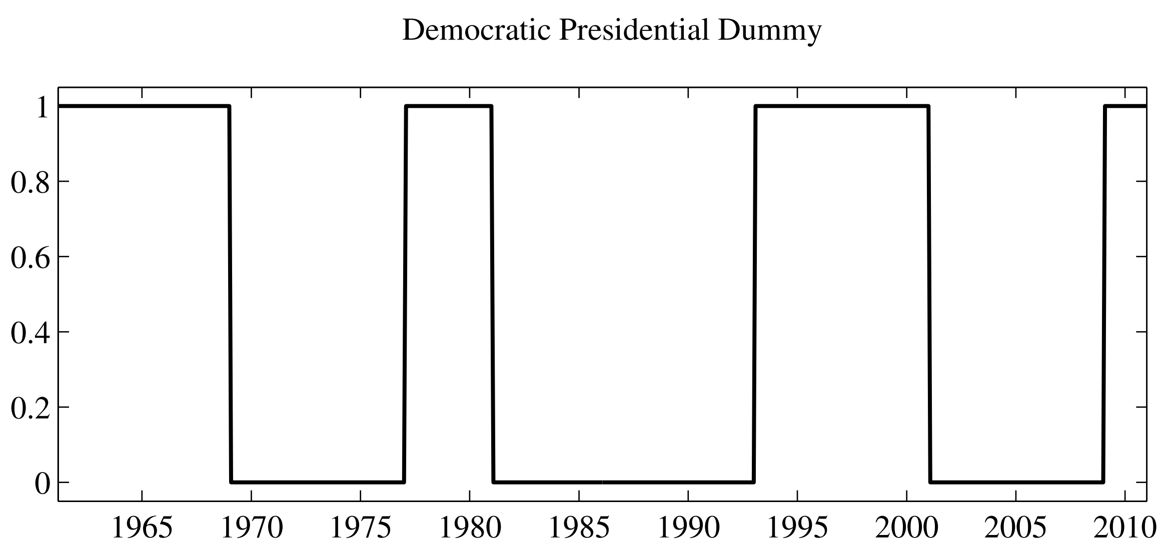

Figure 5. Democrats in the Oval Office
The figure shows a dummy for Democratic presidents, from January 1961 (Kennedy's inauguration) to December 2010.

months that begin with a Republican in the Oval Office, while the market has beaten T-Bills by a highly significant 89 basis points per month in months that started with a Democratic Commander-in-Chief. This 79 basis points per month difference is significant at the 5% level.

Over the same period the smallest decile of stocks (NYSE breaks) has outperformed the largest decile, on a value weighted basis, by 35 basis points per month. This outperformance has, however, come unevenly through time. Small stocks have beaten large stocks by almost a percent per month with Democratic presidents, but actually underperformed large stocks by 10 basis points per month during Republican administrations. The 104

Table 1. The power of presidential party to predict anomaly strategy performance
This table reports the average excess returns ($\mathbf{E}[r^e]$) in percent per month, and results of predictive regressions of the strategies' returns on the predictive variable (PV), a dummy for whether the sitting U.S. President is a Democrat, controlling for investor sentiment as measured by the Baker-Wurgler Index (BWI). Explanatory variables are demeaned. The sample covers January 1961 (the Kennedy inauguration) through December 2010. The Baker-Wurgler Index is available from July 1965. The strategy based on return-on-equity is only available from July 1973, a date determined by the availability of quarterly Compustat data.

Test strategy based on:	$\mathbf{E}[r^e]$	single regressors β_{PV}	single regressors β_{BWI}	multiple regressors β_{PV}	multiple regressors β_{BWI}
Strategies that perform "significantly better" under Democratic Presidents					
Market	0.45	0.79	-0.28	0.78	-0.21
	[2.42]	[2.13]	[-1.41]	[1.90]	[-1.06]
Market equity	0.35	1.04	-0.69	1.03	-0.61
	[1.78]	[2.60]	[-3.25]	[2.31]	[-2.81]
Strategies that perform "significantly better" under Republican Presidents					
Return-on-equity	0.99	-0.97	0.35	-0.92	0.31
	[4.50]	[-2.12]	[1.47]	[-2.00]	[1.30]
Idiosyncratic Vol.	0.57	-2.10	1.27	-1.88	1.11
	[1.98]	[-3.65]	[4.34]	[-3.11]	[3.77]
Betting-Against-Beta	0.88	-1.76	0.53	-1.85	0.38
	[2.46]	[-2.46]	[1.37]	[-2.28]	[0.96]

basis points per month difference is significant at the 1% level.

One explanation for these facts is that Republicans favor big business, and that this is bad for the economy as a whole, but if one accepts this explanation, one must then confront contradictory evidence presented by profitable stocks and stocks with low correlations with the market. Strategies based on return-on-equity (ROE) and Betting-Against-Beta (BAB) perform significantly better under Republican presidents. The ROE strategy is formed on the basis of firms' most recent quarterly earnings relative to their market capitalizations, and is available from July 1973 to December 2010, dates determined by the availability of quarterly earnings data. The ROE strategy yields 1.33% per month under the GOP, four times as much as it does under Democratic presidents. The difference, nearly a percent per month, is significant at the 5% level. Frazzini and Pedersen's (2012) BAB strategy, which buys low beta assets and sells high beta assets, while attempting to stay market-neutral by running each side at a beta of one, has generated 88 basis points per month since Kennedy's inauguration, generating an astounding 165 basis points a month during Republican administrations, but losing 11 basis points a month under Democrats. The difference, 1.76% per month, is significant at the 1% level.

These results are all robust to controlling for sentiment. Including the Baker-Wurgler Index as an explanatory variable has essentially no impact on the coefficient estimates on the presidential dummy in the predictive regressions.

4.2 Predicting anomaly performance with the weather

While it is not entirely impossible that the sitting president can significantly impact market performance, it seems less likely that the weather can do so. Nevertheless, in standard predictive regressions weather-related variables are powerful predictors of anomaly performance.

Figure 6 shows the "predictive" variable used in the next set of regressions, the number of days each month in which the high temperature, as measured at the Central Park weather station, failed to exceed freezing. 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 2010, dates determined by the availability of the

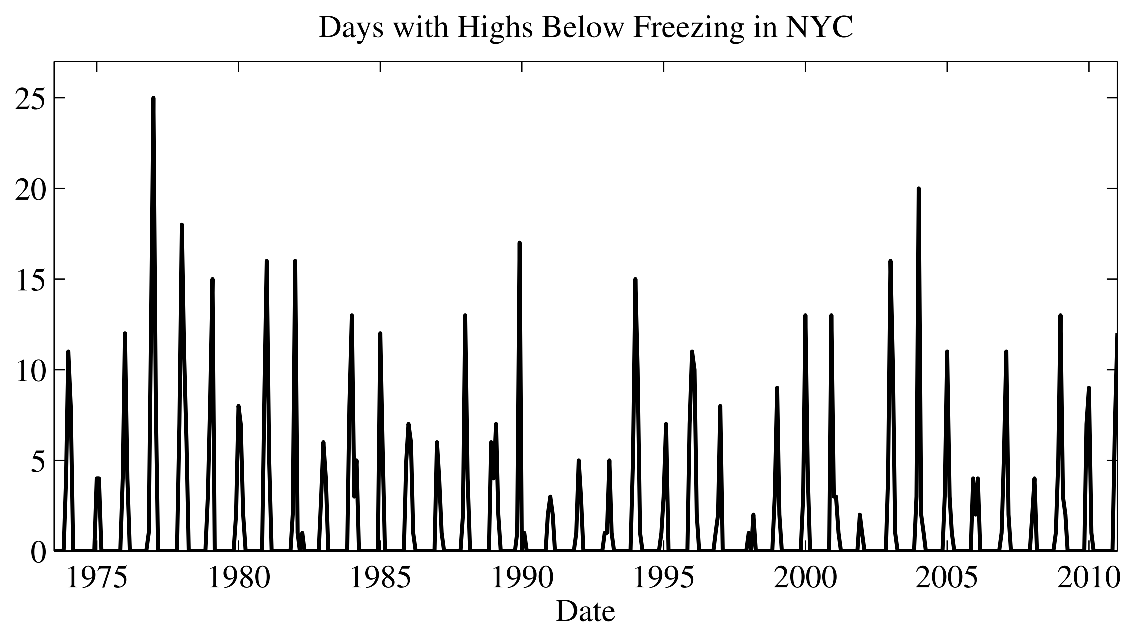

Figure 6. Cold days in New York City
The number of days each month in which the high temperature, as measured at the Central Park weather station, failed to exceed freezing, over the period including July 1973 to December 2010.

quarterly CompuStat data used in the construction of many of the test strategies.

Table 2 shows that cold weather has power predicting the performance of many of the same anomalies as investor sentiment. Cold weather predicts abnormally good performance for small cap strategies, value strategies, strategies based on asset growth and investment, and strategies based on long run reversals. It has significant power predicting abnormally poor performance for many earnings related anomalies, including those based on industry adjusted gross profitability, return on assets, return on equity, gross margins, and earnings momentum, as well as those based on the default measures of Campbell et. al. (2008) and Ohlson (1980).

These results may occur because the weather impacts the "animal spirits" of traders, who predominately live in the New York Metropolitan area. But the weather in Bozeman, Montana, or Hawaii, has about as much power as the weather in New York predicting returns. Taken together these results suggest a seasonality in the performance of many anomaly strategies. A sine wave with an annual periodicity that takes its extremum on the equinox "predicts" the performance of many of the weather related anomalies about as well as cold days in New York. The appendix shows that these results are largely due to a strong January effect, like that documented by Keim (1983) and Reinganum (1983) for small stocks, which is present in many of the anomalies considered here. Table 6, in the Appendix, shows results of regressions of anomaly returns on a January dummy. In general strategies that tend to be long small caps (e.g., those based on book-to-market, asset growth or long run past performance) outperform on average in January, while those that tend to be short small caps (e.g., momentum strategies, those based on any measure of profitability,

Table 2. The weather's power to predict anomaly strategy performance
This table reports the average excess returns ($\mathbf{E}[r^e]$) in percent per month, and results of predictive regressions of the strategies' returns on the predictive variable (PV), the number of days in the previous month that the high temperature in New York's Central Park failed to exceed freezing, controlling for investor sentiment as measured by the Baker-Wurgler Index (BWI). Explanatory variables are demeaned. The sample covers July 1973 through December 2010, and is determined by the availability of the quarterly data used in the construction of many of the strategies.

Test strategy		single regressors		multiple regressors	
based on:	$\mathbf{E}[r^e]$	β_{PV}	β_{BWI}	β_{PV}	β_{BWI}
		Strategies that have performed "significantly better" after cold months			
Market equity	0.35	0.36	-0.60	0.35	-0.53
	[1.53]	[5.84]	[-2.50]	[5.72]	[-2.25]
Book-to-market	0.58	0.17	-0.16	0.17	-0.12
	[3.13]	[3.30]	[-0.80]	[3.26]	[-0.62]
Asset growth	0.70	0.22	-0.00	0.22	0.04
	[4.17]	[4.72]	[-0.02]	[4.73]	[0.26]
Investment	0.61	0.18	-0.02	0.18	0.01
	[3.81]	[4.08]	[-0.14]	[4.08]	[0.09]
Long run past	0.45	0.29	-0.01	0.29	0.05
performance	[1.81]	[4.20]	[-0.05]	[4.20]	[0.19]
		Strategies that have performed "significantly worse" after cold months			
Ind. adj. profitability	0.21	-0.07	0.25	-0.06	0.24
	[2.34]	[-2.69]	[2.67]	[-2.56]	[2.53]
Return-on-assets	0.67	-0.30	0.82	-0.28	0.76
	[2.81]	[-4.54]	[3.30]	[-4.40]	[3.11]
Return-on-equity	1.02	-0.13	0.33	-0.13	0.31
	[4.47]	[-2.09]	[1.39]	[-2.02]	[1.27]
Gross margins	0.02	-0.16	0.35	-0.15	0.32
	[0.15]	[-3.82]	[2.26]	[-3.71]	[2.07]
SUE	0.69	-0.10	0.09	-0.10	0.07
	[4.00]	[-2.04]	[0.47]	[-2.01]	[0.36]
Failure probability	0.76	-0.45	1.53	-0.42	1.44
	[2.09]	[-4.49]	[4.03]	[-4.33]	[3.85]
Ohlson's O-score	0.11	-0.20	0.66	-0.19	0.62
	[0.58]	[-3.95]	[3.42]	[-3.79]	[3.25]

and those that sell distressed firms) underperform on average in January. While these results are interesting in and of themselves, their relevance here stems from their implications for the predictive regressions. Predictive regressions that ignore the seasonality in these anomalies are misspecified, and biased toward rejecting the irrelevance of any "predictive" variable that has a seasonable component.

4.3 Other climatic predictors

While variables with a seasonal component are powerful predictors of anomaly performance, non-seasonal climatic variables are also have significant power predicting anomaly performance. Figure 7 shows the evolution of our next set of predictive variables, the global temperature anomaly ("global warming"), the quasiperiodic Pacific temperature anomaly known as El Niño, and the non-seasonal atmospheric pressure anomaly known as the Arctic Oscillation. 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°-80° West, from the average measured over a 1971-2000 base period. Panel C shows monthly deviations of northern atmospheric pressure from the average measured over a 1971-2000 base period. The global temperature anomaly data come from NASA's Goddard Institute for Space Studies (http://data.giss.nasa.gov/gistemp/), while the El Niño and Arctic Oscillation data come from the NOAA (http://www.cpc.ncep.noaa.gov/data/indices/).

Table 3 shows the power these variables have predicting anomaly performance, including again many of the anomalies previously prominent in the sentiment literature. Panel A

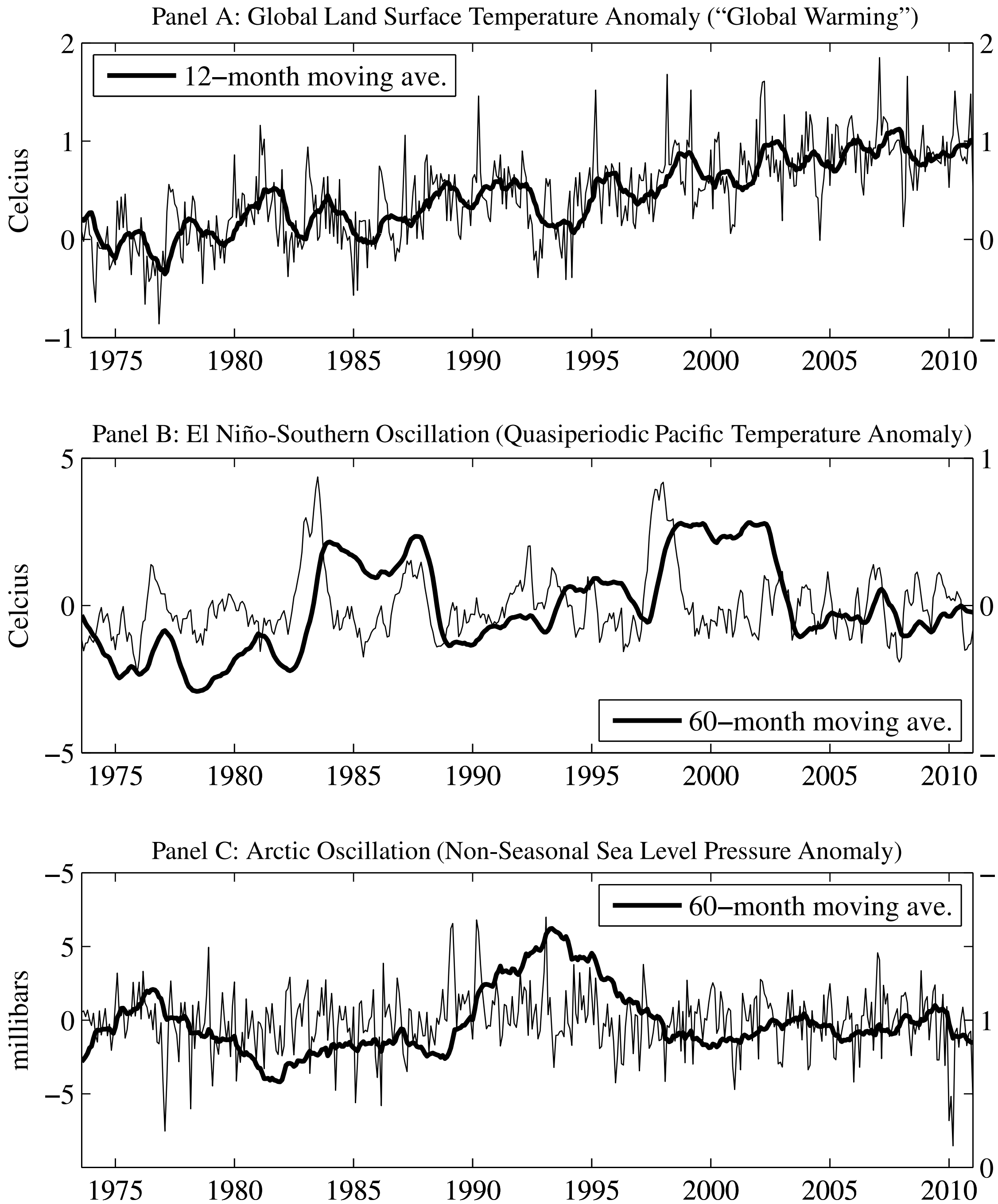

Figure 7. Other Climatic Variables

The figure shows the levels of three non-seasonal climatic “predictive 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; and Panel C shows abnormal Arctic atmospheric pressure. The data cover July 1973 to December 2010.

Table 3. Climatic variables' power to predict anomaly strategy performance

This table reports the average excess returns ($\mathbf{E}[r^e]$) in percent per month, and results of predictive regressions of the strategies' returns on predictive variables (PV), the global temperature anomaly (global warming), the quasiperiodic Pacific temperature anomaly (El Niño), and the non-seasonal northern sea level pressure anomaly (Arctic Oscillation), controlling for investor sentiment as measured by the Baker-Wurgler Index (BWI). Explanatory variables are demeaned. The sample covers July 1973 through December 2010, and is determined by the availability of the quarterly data used in the construction of many of the strategies.

Test strategy based on:	$\mathbf{E}[r^e]$	single regressors β_{PV}	single regressors β_{BWI}	multiple regressors β_{PV}	multiple regressors β_{BWI}
Panel A1: Global Temperature Anomaly as predictive variable					
Value	0.58	-1.10	-0.16	-1.08	-0.04
	[3.13]	[-2.67]	[-0.80]	[-2.55]	[-0.20]
Return-on-equity	1.02	-1.15	0.33	-1.38	0.48
	[4.47]	[-2.27]	[1.39]	[-2.67]	[1.97]
Panel A2: Global Temperature Anomaly 12-month moving average as predictive variable					
Value	0.58	-1.38	-0.16	-1.36	-0.02
	[3.13]	[-2.54]	[-0.80]	[-2.41]	[-0.11]
Gross margins	0.02	0.88	0.35	0.66	0.29
	[0.15]	[2.01]	[2.26]	[1.45]	[1.77]
Investment	0.61	-1.09	-0.02	-1.16	0.09
	[3.81]	[-2.31]	[-0.14]	[-2.36]	[0.51]
Panel B1: El Niño as predictive variable					
Accruals	0.37	0.32	-0.02	0.33	-0.08
	[2.35]	[2.20]	[-0.11]	[2.24]	[-0.47]
Panel B2: El Niño 60-month moving average as predictive variable					
Ind. adj. profitability	0.21	0.78	0.25	0.49	0.15
	[2.34]	[2.70]	[2.67]	[1.32]	[1.26]
Gross margins	0.02	1.31	0.35	1.04	0.14
	[0.15]	[2.73]	[2.26]	[1.67]	[0.72]
Failure probability	0.76	3.27	1.53	0.52	1.42
	[2.09]	[2.77]	[4.03]	[0.35]	[2.92]
Ohlson's O	0.11	1.71	0.66	0.72	0.51
	[0.58]	[2.87]	[3.42]	[0.94]	[2.08]
Net Stock Issuance	0.73	1.92	0.47	1.66	0.13
	[5.15]	[4.25]	[3.18]	[2.87]	[0.71]
Panel C1: Arctic Oscillation Index 60-month moving average as predictive variable					
Net Stock Issuance	0.73	-1.33	0.47	-0.76	0.42
	[5.15]	[-2.03]	[3.18]	[-1.12]	[2.69]
12-month	0.91	2.32	-0.44	1.90	-0.31
	[4.58]	[2.53]	[-2.12]	[1.98]	[-1.42]
Panel C2: Arctic Oscillation Index 120-month moving average as predictive variable					
Book-to-market	0.58	-3.29	-0.16	-3.21	-0.09
	[3.13]	[-2.71]	[-0.80]	[-2.62]	[-0.47]
Gross margins	0.02	2.63	0.35	2.39	0.31
	[0.15]	[2.70]	[2.26]	[2.44]	[1.95]

shows that global warming is bad for value strategies, both those based on book-to-market and earnings-to-price, even after controlling for sentiment. A 12-month moving average of the global temperature anomaly, which takes out its seasonal component, also predicts poor stock price performance for firms that invest a lot, but good performance for firms with market power, though the power of the variable to predict the performance of this last strategy appears to come form its common variation with sentiment.

Panel B shows that warm ocean temperatures in the East Pacific are a significant predictor of good performance for Sloan's (1999) accrual based strategies. A 60-month moving average, which smoothes the temperatures over the basic five year periodicity of the phenomena, predicts strong performance for many of the same anomalies Stambaugh, Yu and Yuan (2012) relate to the Baker-Wurgler Index: those based on 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.

Regressions that control for both the five year moving average of the East Pacific temperature anomaly and the level of investment sentiment, as measured by the Baker-Wurgler Index, suggest that El Niño's power to predict the performance of the distress anomalies derives from its correlation with investor sentiment, but that sentiment's power to predict the performance of the net stock issuance strategy derives from its correlation with El Niño. Including BWI as an explanatory variable dramatically reduces the coefficient on El Niño in the regressions explaining the returns to the distress anomalies, while leaving the coefficient on BWI largely unchanged from its univariate estimate, while including El Niño as an explanatory variable dramatically reduces the coefficient on sentiment when explaining the returns to the issuance anomalies, while leaving the coefficient on El Niño largely unchanged from its univariate estimate.

Panel C shows that a 60-month moving average of the Arctic atmospheric pressure anomaly predicts strong performance for the 12-month strategy of Heston and Sadka (2008), but poor performance for the strategy based on net stock issuance. Its 120-month moving average predicts poor performance for value, but strong performance for the strategy based on market power.

4.4 Celestial predictors of anomaly performance

The planets and stars are also powerful predictors of anomaly performance. Both the planetary aspects (i.e., the apparent proximity of two planets in the heavens to an earth observer) and sunspot activity are powerful predictors of anomaly performance. These anomalies again include many of those prominent in the sentiment literature.

The aspects of Mercury and Venus with the outer planets appear to be particularly important in the data for the performance of anomalies, predicting the performance of strategies based on market cap, book-to-market, momentum, gross profitability, return-on-assets, market power, earnings surprises, failure probability, default probability, idiosyncratic volatility, asset growth, and long run reversals. The aspects of the inner planets with the outer planets have periodicities of roughly a year, however, so it is difficult to distinguish if these variables have power in their own right, or if their power simply derives from their correlation with the weather. I will consequently focus on the aspects of Saturn, and in particular with its celestial relations to Mars and Jupiter. These relations are shown in Pan-

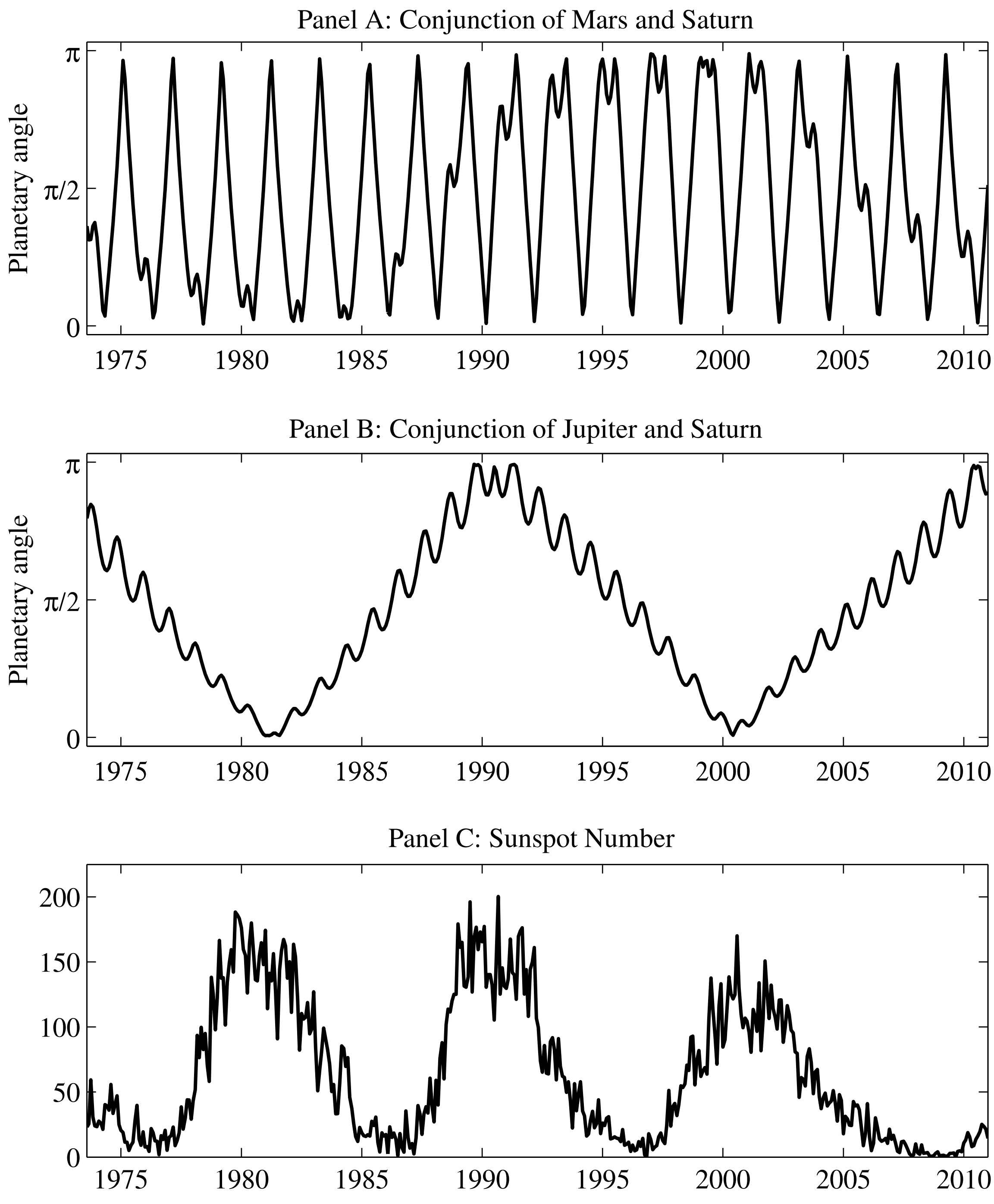

Figure 8. Celestial phenomena

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, and Panel C shows the number of sunspots observed each month. The data cover July 1973 to December 2010.

els A and B of Figure 8. The major periodicity of the aspects are 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 (http://ssd.jpl.nasa.gov/?planet_pos). The figure also shows the level of sunspot activity (Panel C). 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 are available there (http://solarscience.msfc.nasa.gov/greenwch/spot_num.txt).

Panel A of Table 4 shows that the aspect of Mars and Saturn is a powerful predictor of the anomaly performance. The market performs better when Mars and Saturn are in conjunction (i.e., when they appear in close proximity to an earth observer). Small cap strategies and long run reversals also perform better when Mars and Saturn's energies are strongly blended. Strategies based on return-on-assets, return-on-equity, and the failure probability measure of Campbell et. al. (2008) perform better when Mars and Saturn are opposed, perhaps reflecting difficulties that distressed and unprofitable stocks experience when these planets' energies are polarized. The aspect of Mars and Saturn is essentially orthogonal to sentiment, and controlling for sentiment consequently has no impact on these results.

Panel B shows that strategies based on market cap, net stock issuance, asset growth, and investment all perform better when Jupiter and Saturn are opposed. These data suggest that

Table 4. Celestial phenomena and anomaly strategy performance

This table reports the average excess returns ($\mathbf{E}[r^e]$) in percent per month, and results of predictive regressions of the strategies returns on predictive variables (PV), the angle between Mars and Saturn to an earth observer, the angle between Jupiter and Saturn to an earth observer, and the observed number of sunspots, controlling for investor sentiment as measured by the Baker-Wurgler Index (BWI). Explanatory variables are demeaned. The sample covers July 1973 through December 2010, dates determined by the availability of quarterly accounting data employed in many of the strategies' construction.

Test strategy based on:	$\mathbf{E}[r^e]$	single regressors β_{PV}	single regressors β_{BWI}	multiple regressors β_{PV}	multiple regressors β_{BWI}
Panel A: Angle between Mars and Saturn as predictive variable					
Strategies that perform "significantly better" when Mars and Saturn are in conjunction					
Market	0.50	0.60	-0.19	0.61	-0.22
	[2.23]	[2.56]	[-0.80]	[2.60]	[-0.93]
Market equity	0.35	0.51	-0.60	0.54	-0.63
	[1.53]	[2.10]	[-2.50]	[2.23]	[-2.61]
Long run reversals	0.45	0.53	-0.01	0.53	-0.04
	[1.81]	[2.02]	[-0.05]	[2.02]	[-0.15]
Strategies that perform "significantly better" when Mars and Saturn are opposed					
Return-on-assets	0.67	-0.57	0.82	-0.61	0.85
	[2.81]	[-2.26]	[3.30]	[-2.45]	[3.43]
Return-on-equity	1.02	-0.56	0.33	-0.58	0.36
	[4.47]	[-2.33]	[1.39]	[-2.40]	[1.51]
Failure probability	0.76	-0.93	1.53	-1.00	1.58
	[2.09]	[-2.40]	[4.03]	[-2.64]	[4.17]
Idiosyncratic Vol.	0.54	-0.95	1.29	-1.01	1.34
	[1.62]	[-2.68]	[3.69]	[-2.90]	[3.86]
Panel B: Angle between Jupiter and Saturn as predictive variable					
Market equity	0.35	-0.55	-0.60	-0.85	-0.86
	[1.53]	[-2.11]	[-2.50]	[-3.11]	[-3.39]
Net Stock Issuance	0.73	-0.53	0.47	-0.41	0.35
	[5.15]	[-3.35]	[3.18]	[-2.47]	[2.24]
Asset Growth	0.70	-0.60	-0.00	-0.67	-0.20
	[4.17]	[-3.18]	[-0.02]	[-3.36]	[-1.10]
Investment	0.61	-0.40	-0.02	-0.45	-0.16
	[3.81]	[-2.18]	[-0.14]	[-2.35]	[-0.89]
Panel C1: Sunspot number as predictive variable					
UMD	0.67	0.91	0.20	0.88	0.12
	[3.08]	[2.25]	[0.86]	[2.14]	[0.52]
PEAD	0.69	0.72	0.09	0.72	0.02
	[4.00]	[2.27]	[0.47]	[2.22]	[0.12]
Panel C2: Sunspot number cyclic moving average as predictive variable					
Market equity	0.35	-7.53	-0.60	-6.23	-0.38
	[1.53]	[-3.20]	[-2.50]	[-2.48]	[-1.49]
Ohlson's O-score	0.11	7.07	0.66	5.49	0.46
	[0.58]	[3.77]	[3.42]	[2.75]	[2.27]
12-month	0.91	4.81	-0.44	7.21	-0.70
	[4.58]	[2.36]	[-2.12]	[3.35]	[-3.18]

polarization between Jupiter and Saturn may portend difficulties with growth, and should perhaps be taken as a sign to delay plans for rapid expansion. The aspect of Jupiter and Saturn also explains more than ten percent of the variation in the Baker-Wurgler Index, but this seems largely unrelated to the power that either series has predicting anomaly performance. Regressions that employ both variables in all cases yield slope estimates that are similar to their univariate estimates.

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 increase investors' propensity to underreact, slowing down the rate at which news gets incorporated into prices. Strategies that trade on recent past performance and earnings surprises consequently have returns that are significantly positively correlated with the number of sunspots observed in the previous month. These results are again robust to controlling for sentiment.

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 cycle, predicts the performance strategies based on market capitalization, Ohlson's O-score, and seasonalities in stock performance. Unusually intense solar cycles seem to predict poor performance for small caps, but strong performance for strategies that bet on stocks that performed well in the same calendar month in preceding years, or against high default probability stocks. These results cannot be explained by investor sentiment, while much of investor sentiment's power to explain the performance of small cap strategies appears to be explained by its correlation with the intensity of the preceding solar cycle.

5 Alternative Tests

While the preceding sections clearly illustrate the potential for spurious regression bias even when working with returns, they provide no guidance to the researcher interested in running predictive regressions. Plosser and Schwert (1978) suggest that comparisons between regressions run in levels and differences provide a crude test of model specification. First differences in realized returns provide a noisy proxy for changes is expected returns, which are much less persistent than their level, alleviating spurious regression bias concerns. First-differencing greatly reduces the variation in the predictive variable, however, without reducing the variation in realized returns, lowering the signal to noise ratio and yielding less powerful tests. While regressions run in first differences are more likely to be well specified, realistic samples are not large enough to allow regressions run in differences to identify significant return relations. Similar limitations apply to other standard methods for handling persistent regressors. Ferson, Sarkissian and Simin (2008) find that available return series are too short to admit sufficient lags to correct the spurious regression bias using the Newey-West procedure, and lagged returns are a poor instrument for the persistence in excess returns. The extensive literature on small-sample distributions offers no solutions, because the problem is ultimately one of potential misspecification.

Without an obvious methodological correction for potential misspecification bias, the econometrician estimating predictive regressions should at least report results from simulations using similarly persistent regressors. If one admits the possibility that expected returns are persistent, but vary over time for reasons potentially unrelated to the predictive variable, then inferring significance directly from standard test-statistics is impossible.

Results cannot be considered significant if the test-statistic observed on the predictive variable is not unusual among similarly persistent predictors. Statistical significance requires that the observed test-statistic is extreme in the empirical distribution of test-statistics from predictive regressions using random regressors with autocorrelation structures similar to that observed in the candidate predictive variable. Note that this is only a necessary condition, not sufficient condition, for true significance. Reporting these results does not fully address concerns regarding spurious regression bias, as it is always possible that the autocorrelation structure chosen for the random regressors misses an important dimension of the persistence in the expected returns. Researchers looking to find predictive variables are more likely to find spurious regressors with the right structure.

The next set of tests consider the power of investor sentiment and past market performance predicting the performance of anomalies relative to similarly persistent randem regressors. Figure 9 shows autocorrelations for the Baker-Wurgler Index over our sample, July 1973 to December 2010, for monthly lags out to 20 years. It also shows the autocorrelations for a pseudo-periodic AR(2) process with a periodicity of 187 months ($a_2 = 0.981$ and $a_1 = \sqrt{-a_2}\cos(2\pi/187)$), which roughly matches the autocorrelation structure observed in investor sentiment. The AR(2) is too smooth, and consequently has autocorrelations that are too high at short horizons, features that could be addressed by adding transitory noise.

Table 5 shows results of predictive regressions employing the Baker-Wurgler Index (BWI) and the cumulative five year market excess return ($\text{MKT}_{60,1}$) as the predictive variables. The table reports both OLS test-statistics, and test-statistics scaled by the standard

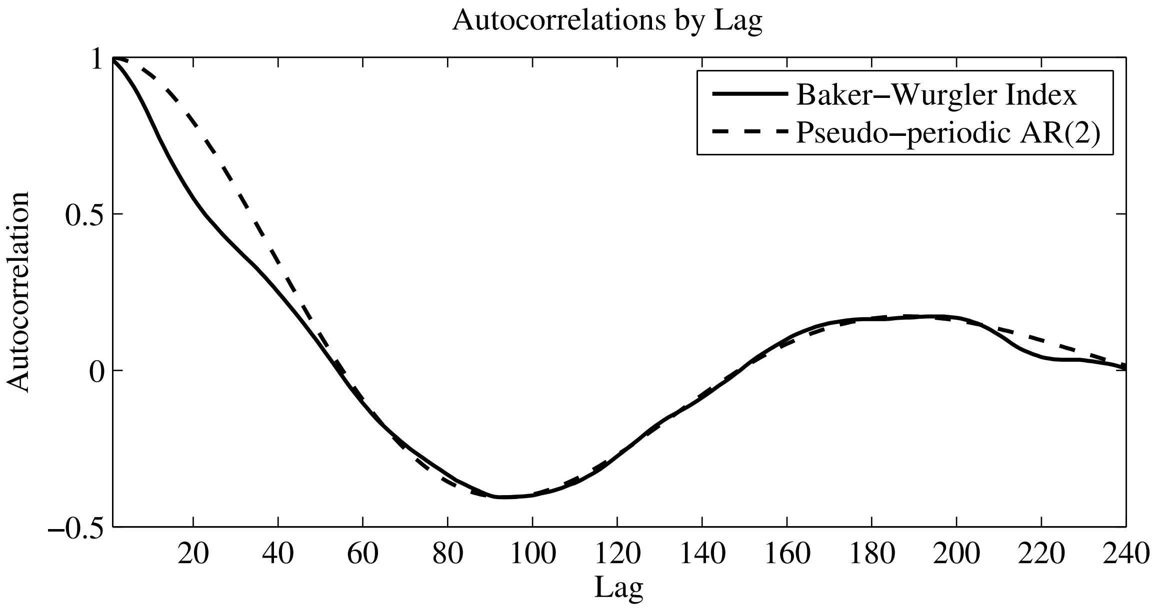

Figure 9. Baker-Wurgler Index Sample Autocorrelations
The figure shows the correlogram for the Baker-Wurgler Index over the sample July 1973 to December 2010, for lags out to 240 months (solid line). It also shows the correlogram for a pseudo-periodic autoregressive AR(2) process with a periodicity of 187 months($a_2 = 0.981$ and $a_1 = \sqrt{-a_2}\cos(2\pi/187)$).

deviation of the empirical distribution of test-statistics from tests employing randomly generated regressors. The test-statistics on the estimated slope coefficients on BWI are adjusted using the empirical distribution from tests employing the pseudo-periodic AR(2) regressors with a periodicity of 187 months shown in Figure 9. Those on $\text{MKT}_{60,1}$ are adjusted using the empirical distribution from tests employing a 60-month moving average of white noise, a good approximation of realized five year log returns. In the multiple regressions the simulated regressors are generated using the same shocks, to reflect the fact that market sentiment and past market performance are positively correlated in the data.

The table shows that while market sentiment appears to have more power than the random regressors predicting the performance of the strategy based on idiosyncratic volatility

Table 5. Past market performance and anomaly strategy performance
This table reports the average excess returns ($\mathbf{E}[r^e]$) in percent per month, and results of predictive regressions of the strategies' returns on predictive variables, the Baker-Wurgler Index (BWI) and the market's cumulative five year excess log-return ($\text{MKT}_{60,1}$). The table reports both standard OLS test-statistics (first set of brackets), and test-statistics scaled by the standard deviation of the empirical distribution of test-statistics using simulated regressors with similar autocorrelations (pseudo-periodic AR(2) for the BWI and a 60 month moving average for $\text{MKT}_{60,1}$). The sample covers July 1973 through December 2010, dates determined by the availability of quarterly accounting data employed in many of the strategies' construction.

Test strategy based on:	$\mathbf{E}[r^e]$	single regressors β_{BWI}	single regressors $\beta_{\text{MKT}_{60,1}}$	multiple regressors β_{BWI}	multiple regressors $\beta_{\text{MKT}_{60,1}}$
Strategies that perform better when sentiment is high					
Ind. adj. profitability	0.21	0.25	0.80	0.15	0.56
	[2.34]	[2.67]	[2.84]	[1.39]	[1.69]
		[2.59]	[2.58]	[1.33]	[1.51]
Return-on-assets	0.67	0.82	2.60	0.51	1.79
	[2.81]	[3.30]	[3.46]	[1.75]	[2.03]
		[4.24]	[3.90]	[2.09]	[2.16]
Gross margins	0.02	0.35	1.18	0.21	0.85
	[0.15]	[2.26]	[2.50]	[1.11]	[1.54]
		[1.76]	[1.80]	[1.02]	[1.27]
Failure probability	0.76	1.53	5.51	0.78	4.27
	[2.09]	[4.03]	[4.85]	[1.77]	[3.20]
		[3.50]	[4.13]	[1.66]	[2.93]
Ohlson's O-score	0.11	0.66	2.64	0.27	2.21
	[0.58]	[3.42]	[4.61]	[1.21]	[3.28]
		[2.14]	[3.03]	[0.87]	[2.50]
Net stock issuance	0.73	0.47	1.30	0.34	0.76
	[5.15]	[3.18]	[2.91]	[1.94]	[1.46]
		[1.48]	[1.68]	[0.96]	[0.93]
Idiosyncratic Vol.	0.54	1.29	3.26	0.99	1.68
	[1.62]	[3.69]	[3.09]	[2.43]	[1.36]
		[3.44]	[2.83]	[2.49]	[1.37]
Strategies that perform better when sentiment is low					
Market equity	0.35	-0.60	-1.88	-0.38	-1.27
	[1.53]	[-2.50]	[-2.58]	[-1.35]	[-1.48]
		[-1.42]	[-1.54]	[-0.87]	[-1.02]
12-month	0.91	-0.44	0.08	-0.63	1.09
	[4.58]	[-2.12]	[0.13]	[-2.58]	[1.47]
		[-1.35]	[0.09]	[-1.77]	[1.10]
Strategies predicted by past market performance but not by sentiment					
Momentum	1.43	0.31	3.98	-0.53	4.82
	[4.28]	[0.88]	[3.79]	[-1.29]	[3.90]
		[1.26]	[4.54]	[-1.69]	[4.41]
SUE	0.69	0.09	1.22	-0.18	1.50
	[4.00]	[0.47]	[2.23]	[-0.82]	[2.33]
		[0.52]	[2.26]	[-0.95]	[2.44]
Book-to-market	0.58	-0.16	-1.36	0.11	-1.53
	[3.13]	[-0.80]	[-2.29]	[0.47]	[-2.20]
		[-0.63]	[-1.64]	[0.37]	[-1.58]

and earnings related anomalies (i.e., those formed on the basis of industry adjusted gross profitability, return-on-assets, failure probability, and default probability), its power to predict the performance of strategies based on size, net stock issuance, market power, and seasonality is unremarkable among similarly persistent random regressors. Similar results hold using past market performance as the predictive variable. Past market performance additionally appears to have more power than a 60-month moving average of white noise predicting the performance of both price and earnings momentum, but its power to predict the performance of value is unremarkable among similarly persistent random regressors. The table also shows that the power BWI has predicting the performance of the earnings related anomalies, including those formed on the basis of failure and default probabilities, is largely explained by its correlation with past market performance.

6 Conclusion

When expected returns are persistent, then misspecified predictive regressions are biased toward rejecting the independence of returns and any persistent variable. The data suggest that these concerns are more than theoretical. Predictive regressions of real anomaly returns on persistent variables frequently find a significant relation, even when the two series are clearly unrelated.

Running predictive regressions in first difference is much safer. These regressions have less power, and are consequently less attractive to those seeking to find significant predictive variables, but have the enormous advantage of yielding meaningful answers. The misspecified regression bias is ultimately just an issue of power. Persistence in expected returns reduces the number of effective observations, and ignoring this fact results in test that overstate the significance of their results. It is simply harder to find variables that truly have power to predict anomaly performance than it is to find variables that appear to have power in misspecified OLS regressions.

A Appendix: Additional Tables

Table 6. January effect in anomaly strategy performance

This table reports the average excess returns ($\mathbf{E}[r^e]$) in percent per month, and results of predictive regressions of the strategies returns on the predictive variable (PV), a January dummy, controlling for investor sentiment as measured by the Baker-Wurgler Index (BWI). Explanatory variables are demeaned. The sample covers July 1973 through December 2010, dates determined by the availability of quarterly accounting data employed in many of the strategies' construction.

Test strategy based on:	$\mathbf{E}[r^e]$	single regressors β_{PV}	single regressors β_{BWI}	multiple regressors β_{PV}	multiple regressors β_{BWI}
Strategies that perform significantly better in January					
Market equity	0.35	5.41	-0.60	5.41	-0.61
	[1.53]	[6.79]	[-2.50]	[6.84]	[-2.63]
Book-to-market	0.58	1.54	-0.16	1.55	-0.16
	[3.13]	[2.29]	[-0.80]	[2.29]	[-0.81]
Asset growth	0.70	1.99	-0.00	1.99	-0.00
	[4.17]	[3.29]	[-0.02]	[3.29]	[-0.02]
12-month	0.91	1.92	-0.44	1.92	-0.44
	[4.58]	[2.68]	[-2.12]	[2.70]	[-2.14]
Long run past performance	0.45	4.64	-0.01	4.64	-0.02
	[1.81]	[5.27]	[-0.05]	[5.26]	[-0.06]
Strategies that perform significantly worse in January					
Momentum	1.43	-3.78	0.31	-3.78	0.31
	[4.28]	[-3.14]	[0.88]	[-3.14]	[0.90]
Ind. adj. profitability	0.21	-0.74	0.25	-0.74	0.25
	[2.34]	[-2.29]	[2.67]	[-2.31]	[2.69]
Return-on-assets	0.67	-4.38	0.82	-4.39	0.83
	[2.81]	[-5.19]	[3.30]	[-5.26]	[3.40]
Return-on-equity	1.02	-3.06	0.33	-3.06	0.34
	[4.47]	[-3.74]	[1.39]	[-3.75]	[1.41]
Gross margins	0.02	-1.28	0.35	-1.28	0.35
	[0.15]	[-2.38]	[2.26]	[-2.39]	[2.27]
SUE	0.69	-2.28	0.09	-2.28	0.09
	[4.00]	[-3.70]	[0.47]	[-3.70]	[0.48]
Failure probability	0.76	-8.37	1.53	-8.37	1.53
	[2.09]	[-6.59]	[4.03]	[-6.72]	[4.23]
Ohlson's O-score	0.11	-2.22	0.66	-2.22	0.66
	[0.58]	[-3.36]	[3.42]	[-3.40]	[3.46]
Idiosyncratic Vol.	0.54	-3.71	1.29	-3.72	1.29
	[1.62]	[-3.09]	[3.69]	[-3.13]	[3.73]

References

[1] Baker, Malcolm, and Jeffery Wurgler, 2000, “The equity share in new issues and aggregate stock returns,” *Journal of Finance* 55, 2219-2257.

[2] Baker, Malcolm, and Jeffery Wurgler, 2006, “Investor Sentiment and the Cross-Section of Stock Returns,” *Journal of Finance* 55, 1645-1680.

[3] Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, “In Search of Distress Risk,” *Journal of Finance* 63, 2899-2939.

[4] Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, “Market States and Momentum,” *Journal of Finance* 59, 1345-1365.

[5] Fama, E.F., and Kenneth R. French, 1988, “Dividend yields and expected stock returns,” *Journal of Financial Economics* 22, 3-25.

[6] Fama, Eugene F., and Kenneth R. French, 1993, “Common Risk Factors in the Returns on Stocks and Bonds,” *Journal of Financial Economics* 33, 3-56.

[7] Fama, E.F., and G. William Schwert, 1977, “Asset returns and inflation,” *Journal of Financial Economics* 5, 115-146.

[8] Ferson, W., Sarkissian, S., Simin, T., 2003, “Spurious regressions in Financial economics” *Journal of Finance* 58, 1393-1413.

[9] 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.

[10] Foster, F. Douglas,Tom Smith, and Robert E.Whaley, 1997, ‘Assessing goodness-of-t of asset pricing models: The distribution of the maximal R-squared,” *Journal of Finance* 52, 591-607.

[11] Frazzini, Andrea, and Lasse Pedersen, 2012, “Betting Against Beta,” working paper.

[12] Granger, Clive W. J., and Paul Newbold, 1974, “Spurious regressions in economics,” *Journal of Econometrics* 4, 111-120.

[13] Heston, Stenven J., and Ronnie Sadka, 2008, “Seasonality in the cross-section of stock returns,” *Journal of Financial Economics* 87, 418-445.

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

[15] Lamont, Owen A., and Jeremy C. Stein, 2004, “Aggregate Short Interest and Market Valuations,” *American Economic Review,* 94, 29-32.

[16] Lemmon M., Portniaquina, E., 2006, “Consumer confidence and asset prices: some empirical evidence,” *Review of Financial Studies* 19, 1499-1529.

[17] Lettau, Martin, and Sydney Lugvigson, 2001, "Consumption, Aggregate Wealth, and Expected Stock Returns," *Journal of Finance* 56, 815-849.

[18] Novy-Marx, Robert, 2012, "The Other Side of Value: the Gross Profitability Premium," working paper.

[19] Ohlson, James A., 1980, "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research* 18, 109-131.

[20] Plosser, Charles I., and G. William Schwert, 1978, "Money, Income and Sunspots: Measuring Economic Relationships and the Effects of Differencing," *Journal of Monetary Economics* 4, 637-660.

[21] 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.

[22] Schwert, G. William, 2003, "Anomalies and Market Efficiency," Chapter 15 in Handbook of the Economics of Finance, eds. George Constantinides, Milton Harris, and Rene M. Stulz, North-Holland, 937-972.

[23] Stambaugh, Robert F., 1999, "Predictive Regressions," *Journal of Financial Economics* 54, 375421.

[24] Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, "The Short of It: Investor Sentiment and Anomalies" *Journal of Financial Economics* 104, 288302.

[25] Standish, E.M. (JPL/Caltech), "Keplerian Elements for Approximate Positions of the Major Planets," available from the JPL Solar System Dynamics web site (http://ssd.jpl.nasa.gov/).