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The long of it: Odds that investor sentiment spuriously predicts anomaly returns☆

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ABSTRACT

Extremely long odds accompany the chance that spurious-regression bias accounts for investor sentiment's observed role in stock-return anomalies. We replace investor sentiment with a simulated persistent series in regressions reported by Stambaugh, Yu, and Yuan (2012), who find higher long-short anomaly profits following high sentiment, due entirely to the short leg. Among 200 million simulated regressors, we find none that support those conclusions as strongly as investor sentiment. The key is consistency across anomalies. Obtaining just the predicted signs for the regression coefficients across the 11 anomalies examined in the above study occurs only once for every 43 simulated regressors.

1. Introduction

Caution is warranted when inferring that a highly autocorrelated variable can predict asset returns. One reason is the possibility of a "spurious" regressor: If the unobserved expected return on an asset is time-varying and persistent, another persistent variable having no true relation with return can appear to predict return in a finite sample. Ferson, Sarkissian, and Simin (2003) demonstrate how the potential for such regressors complicates the task of assessing return predictors, and they explain how the underlying mechanism relates to the spurious-regression problem analyzed by Yule (1926) and Granger and Newbold (1974). Ferson et al. also explain how data mining interacts with the problem of spurious regressors. When the potential for spurious regressors exists (i.e., a persistent time-varying expected return), data mining produces an especially greater chance of finding a series that appears to predict returns but does so only spuriously.

The stronger is the prior motivation for entertaining a series as a return predictor, the weaker is the concern that its apparent predictive ability is spurious.[3] One quantity with

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[3] A regressor with prior motivation also often violates the spurious-regressor setting in Ferson, Sarkissian, and Simin (2003), wherein the regressor bears no relation to return. Instead, the innovation in the regressor is often correlated with contemporaneous return, whether or

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strong prior motivation as a return predictor is market-wide investor sentiment. At least as early as Keynes (1936), numerous authors have considered the possibility that a significant presence of sentiment-driven investors can cause prices to depart from fundamental values, thereby creating a component of future returns that corrects such mispricing. Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012), among others, find that investor sentiment and/or consumer confidence exhibits an ability to predict returns on various classes of stocks and investment strategies.[4] These studies also refine the prior motivation of investor sentiment as a predictor. For example, Baker and Wurgler (2006) argue that sentiment should play a stronger role among stocks that are more difficult to value. In support of that hypothesis, they find sentiment exhibits greater ability to predict returns on small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Stambaugh, Yu, and Yuan (2012) hypothesize that when market-wide sentiment is combined with Miller (1977, 's) argument about the effects of short-sale impediments, overpricing due to high sentiment is more likely than underpricing due to low sentiment. Their results support that argument, in that sentiment predicts profits on the short legs of a large set of anomaly-based long-short strategies, whereas sentiment exhibits no ability to predict long-leg profits.

Despite the prior motivation for the properties that investor sentiment exhibits empirically as a predictor of anomaly returns, one might nevertheless be concerned that sentiment is simply a spurious predictor. Such a concern might be prompted, for example, by the results of Novy-Marx (2014), who reports that returns on various subsets of anomalies can apparently be predicted by seemingly unlikely variables such as sunspots and planetary positions.[5] This study assesses the odds that investor sentiment's observed ability as a predictor can be achieved by a spurious regressor. We focus on the role of consistency across multiple return series and hypotheses. To understand the value of consistency, suppose the true expected returns across a number of portfolios possess some independent variation, but each expected return's true correlation with investor sentiment has the same sign. The greater the number of portfolios, the more difficult it becomes to find a spurious regressor that will exhibit finite-sample predictive ability consistently across portfolios comparable to that of investor sentiment. Our setting for exploring the role of consistency is that of Stambaugh, Yu, and Yuan (2012). That study examines 11 different anomalies and finds consistent results across those anomalies in support of three hypotheses: (i) a positive relation between current sentiment and future long-short return spreads, (ii) a negative relation between current sentiment and future short-leg returns, and (iii) no relation between current sentiment and future long-leg returns. We simply ask how likely it is that such hypotheses are supported as strongly by a randomly generated spurious regressor used in place of investor sentiment.

Out of 200 million simulated regressors, we find none that jointly support the three hypotheses in Stambaugh, Yu, and Yuan (2012) as strongly as investor sentiment. The odds are still quite long if one looks at just one of the three hypotheses. For example, comparably strong and consistent support for the first hypothesis—a positive relation between sentiment and the long-short return spread—occurs once in every 28,500 simulated regressors. For the second hypothesis—a negative relation between sentiment and short-leg returns—comparable support occurs once in every 105,000 regressors. If one sets aside any consideration of strength (t-statistics) and simply looks at the signs of regression coefficients dictated by the first two hypotheses, even then only one in every 43 simulated regressors achieves the consistency exhibited with investor sentiment.

2. Empirical setting and simulation results

The empirical setting we analyze here focuses on the main set of regression results reported by Stambaugh, Yu, and Yuan (2012), hereafter SYY. That study estimates the regression,

$$R_{i,t} = a + bS_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t, \tag{1}$$

where $R_{i,t}$ is the excess return in month t on an anomaly strategy's long leg, short leg, or the difference, S_{t-1} is the level of the investor-sentiment index of Baker and Wurgler (2006) at the end of month $t-1$, and MKT_t, SMB_t, and HML_t are the returns on month t on the three stock-market factors defined by Fama and French (1993). SYY examine 11 anomalies documented previously in the literature:

1. Failure probability (Campbell, Hilscher, and Szilagyi, 2008)
2. Distress (Ohlson, 1980)
3. Net stock issues (Ritter, 1991; Loughran and Ritter, 1995)
4. Composite equity issues (Daniel and Titman (2006))
5. Total accruals (Sloan, 1996)
6. Net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004)
7. Momentum (Jegadeesh and Titman, 1993)
8. Gross profitability (Novy-Marx, 2013)
9. Asset growth (Cooper, Gulen, and Schill, 2008)
10. Return on assets (Fama and French, 2006; Chen, Novy-Marx, and Zhang, 2010; Wang and Yu, 2010)
11. Investment-to-assets (Titman, Wei, and Xie, 2004; Xing, 2008)

As in SYY, the sample period is from August 1965 through January 2008 for all but anomaly (1), whose data begin in

(*footnote continued*)
not the regressor predicts future return. Such a correlation is especially likely for a regressor that is a valuation ratio, such as dividend yield. The finite-sample bias that arises in such a setting is analyzed by Stambaugh (1999).

[4] Other studies that document the ability of sentiment measures to predict returns include Brown and Cliff (2004, 2005), Lemmon and Portniaguina (2006), Baker and Wurgler (2007, 2012), Livnat and Petrovits (2009), Baker, Wurgler, and Yuan (2012), Antoniou, Doukas, and Subrahmanyam (2013), Stambaugh, Yu, and Yuan (2013), and Yu (2013).

[5] Indeed, a preliminary version of that study presented such results in the context of spurious regressors.

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