Scaling up Market Anomalies

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Financial economics have identified a plethora of firm characteristics that predict future stock returns. Such predictability is unexplained by canonical asset pricing models and thus establishes anomalous patterns in the cross-section of average stock returns. However, due to the improvement in market liquidity as well as the learning of investors from academic publications, the profitability of investment strategies that employ predictive characteristics often attenuates and even disappears over time (e.g., Schwert [2003], Chordia, Roll, and Subrahmanyam [2011], and McLean and Pontiff [2016]). The momentum trading strategy of Jegadeesh and Titman [1993] is an exception. In particular, Jegadeesh and Titman [2001, 2002] and Schwert [2003] documented momentum profitability during the post-publication period, and Asness, Moskowitz, and Pedersen [2013] implemented comprehensive enough analyses to show that momentum is a robust anomaly.

This article proposes an active trading strategy that implements momentum among 15 well-known market anomalies. Given that the traditional momentum strategy exploits the persistence in stock prices, we essentially examine whether the same persistence exists in anomaly payoffs and whether the proposed trading strategy outperforms the common benchmarks. To pursue this task, we consider U.S. common stocks over the sample period from 1976 through 2013. Following Stambaugh, Yu, and Yuan [2012] and Avramov et al. [2013], we consider the following anomalies: failure probability, O-score, net stock issuance, composite equity issuance, total accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, abnormal capital investment, standardized unexpected earnings, analyst dispersion, idiosyncratic volatility, and the book-to-market ratio.

Our investment universe consists of stocks in the top (best-performing, long-leg) and bottom (worst-performing, short-leg) anomaly portfolios. To illustrate, the highest gross profitability stocks are in the top portfolio, while the lowest gross profitability stocks are in the bottom portfolio. The same idea applies to all the other anomalies. Essentially, there are 15 top and 15 bottom anomaly portfolios. The top and bottom portfolios are independently sorted into three groups based on their lagged one-month (month $t-1$) returns. The loser (winner) portfolio consists of the bottom (top) five anomalies, while the other five anomalies are in the median group. Our active anomaly-based strategy undertakes a long position in the long-leg winner and a short position in the short-leg loser portfolios. We compare the investment outcome of this active momentum strategy with a naive benchmark that equally invests in all 15 anomalies. In addition, we also consider three and four top and bottom anomaly portfolios, and the overall evidence is unchanged.

In the first place, our experiments show that, consistent with past work, the profitability of individual anomalies diminishes over time, and moreover, such profitability is highly volatile. However, a naive strategy that takes equal positions across all anomalies considerably mitigates the downside risk of investing in individual anomalies, and it exhibits high profitability through the entire sample period. To wit, the Fama–French three-factor adjusted return (alpha) is 0.813% a month in the pre-2000 period and 0.624% in the post-2000 period. Indeed, consistent with Stambaugh, Yu, and Yuan [2012], there is a rather small correlation among anomaly payoffs, which motivates the strategy of combining anomalies.

Notably, our proposed momentum strategy considerably outperforms that naive benchmark. We show that there is a strong positive autocorrelation of anomaly payoffs across different time horizons ranging from one month to five years. Consequently, the active strategy conditioned on past one-month return yields a monthly alpha ranging between 1.273% and 1.471%, indicating a significant 59% to 84% increase comparing with the naive strategy. The proposed momentum trading strategy remains profitable during the post-2000 period generating a monthly alpha ranging between 0.774% and 0.912%.

As a robustness check, we implement our proposed strategy when the conditioning variable is the predicted future return (as opposed to past one-month return). The predicted return is the fitted value emerging from time-series predictive regressions of anomaly payoffs on lagged values of investor sentiment, market illiquidity, and market return. The evidence shows that all these marketwide variables are strong predictors of anomaly payoffs. Moreover, using predictive regressions to estimate future predicted return further improves the investment payoff generated by our proposed momentum strategy. Interestingly, the investor sentiment has uniformly been the best predictor of anomaly payoffs since 2000. In particular, a momentum strategy that conditions on the estimated expected return based on the investor the sentiment predictive variable generates a monthly alpha that ranges between 1.046% and 1.243% in the recent decade.

Finally, we examine the momentum in anomalies conditional on high-versus-low investor sentiment, as the original momentum trading strategy is shown to be profitable only following periods of high investor sentiment due to the presence of optimistic investors and binding short-sale constraints (Stambaugh, Yu, and Yuan [2012]). We find that our proposed momentum strategy yields higher risk-adjusted returns following a high sentiment period. The monthly risk-adjusted return ranges between 1.421% and 1.732% in high sentiment periods, compared with 1.094% to 1.182% when investor sentiment is low.

This study extends the literature on momentum effects in asset prices, and in particular, we investigate the persistence in anomaly payoffs. For one thing, if the return predictability in market anomalies reflects mispricing, this predictability should decay or disappear as long as sophisticated investors are aware of the mispricing opportunity and trade against it (McLean and Pontiff [2016]). If some anomalies display more continuation than others, however, a trend can be identified and exploited during the adjustment period. Of course, anomalies can reflect ongoing behavioral biases of financial market participants and thus their decay can be long lasting. To gauge the economic magnitude of the persistence in anomaly payoffs, we propose an active trading strategy that buys a subset of top anomaly portfolios and sells a subset of bottom anomaly portfolios based on past realized or predicted future returns. The proposed strategy consistently outperforms common benchmarks throughout the entire sample period as well as during the post-2000 period, when many market anomalies are found to be unprofitable. Our results suggest that although the individual anomaly-based strategy becomes less attractive over time, the same set of firm characteristics underlying those anomalies can still be used by asset managers to make sound investment decisions. Overall, our experiments are important in understanding the structure of anomaly payoffs, their dependence on marketwide state variables, as well as the overall practice of asset management in further proving investment vehicles.

DATA AND VARIABLE CONSTRUCTION

Our experiments are based on NYSE, AMEX, and NASDAQ common stocks with Center for Research in Security Prices (CRSP) share codes of 10 or 11. The sample spans the January 1976 through December 2013 period. Daily and monthly common stock data are recorded from the CRSP database, while quarterly and annual financial statement data are from the COMPUSTAT database. Stock returns and accounting data are employed to construct a set of 15 market anomalies following Stambaugh, Yu, and Yuan [2012] and Avramov et al. [2013].

The 15 anomalies consist of failure probability (e.g., Campbell, Hilscher, and Szilagyi [2008], Chen, Novy-Marx, and Zhang [2011]); O-score (Ohlson [1980]); net stock issuance (Ritter [1991], Loughran and Ritter [1995]); composite equity issuance (Daniel and Titman [2006]), total accruals (Sloan [1996]), net operating assets (Hirshleifer et al. [2004]); momentum (Jegadeesh and Titman [1993]); gross profitability (Novy-Marx [2013]); asset growth (Cooper, Gulen, and Schill [2008]); return on assets (Fama and French [2006]); abnormal capital investment (Titman, Wei, and Xie [2004]); standardized unexpected earnings (Chan, Jegadeesh, and Lakonishok [1996]); analyst dispersion (Diether, Malloy, and Scherbina [2002]); idiosyncratic volatility (Campbell et al. [2001]); and book-to-market ratio (Fama and French [1992, 1993]).

The details on the construction of all 15 firm-specific variables underlying all these anomalies are provided in the Appendix. Most anomalies are constructed on an annual basis; while the failure probability, O-score, return on assets, standardized unexpected earnings, and book-to-market ratio are computed quarterly, momentum, analyst dispersion, and idiosyncratic volatility are formed monthly. For anomalies based on information from financial statements, we use the fiscal year-end but consider the accounting variables observable only in June of the next calendar year. We thus avoid any potential look-ahead bias, undertaking a real-time perspective.

Our investment universe is based on 30 portfolios establishing the top (best-performing) and bottom (worst-performing) deciles of each of the 15 anomalies. To construct top and bottom portfolios, all common stocks are sorted into deciles according to the lagged one-month (month $t - 1$) firm-specific variable underlying the anomaly. The top 15 portfolios consist of 10% of the stocks with the lowest failure probability, lowest O-score, lowest net stock issuance, lowest composite equity issuance, lowest total accruals, lowest net operating assets, highest past six-month returns, highest gross profitability, lowest asset growth, highest return on assets, lowest abnormal capital investment, highest standardized unexpected earnings, lowest analyst dispersion, lowest idiosyncratic volatility, *or* highest book-to-market ratio. The bottom 15 portfolios consist of stocks in the opposite extreme deciles. Our proposed trading strategy takes a long position in a subgroup of the best-performing top portfolios along with short position in a subgroup of the worst-performing bottom portfolios. Performance is based on the past one-month return. If indeed anomaly payoffs are persistent, such a momentum trading strategy implemented among anomalies will outperform a more naive strategy that equally weights all anomalies.

Exhibit 1 displays summary statistics on the 15 anomaly portfolios (in the order described previously) as well as an equal-weighted (or naive) combination. Panel A of Exhibit 1 shows payoffs to long–short positions, while Panel B (C) considers exclusively long (short) trading strategies. For each of the 15 anomalies, the month t portfolio holding period return is the value-weighted average of stocks in each decile. We obtain the returns to anomaly-based trading strategy by taking a long position in the top (best-performing) decile and a short position in the bottom (worst-performing) decile. Anomaly returns are further adjusted by the Fama–French three common factors—market (excess return on the value-weighted CRSP market index over the one-month T-bill rate, MKT), size (small minus big return premium, SMB), and value (high book-to-market minus low book-to-market return premium, HML).[1]

Observe from Panel A of Exhibit 1 that of the 15 long–short strategies, 13 strategies produce significantly positive Fama–French three-factor risk-adjusted return over the entire sample period. The average Fama–French three-factor adjusted return for the combined strategy is 0.8% a month. Panel A also presents other characteristics of the portfolios. In particular, the *Sharpe ratio* is computed as the average excess monthly portfolio return divided by its standard deviation over the entire sample period, the *shortfall probability* is defined as the probability of a negative return, and the *value at risk* is the maximal potential loss in the value of the portfolio over one month with a 5% probability. The evidence shows a strong cross-sectional variation in the value at risk ranging from 3.7 to 13, suggesting that betting on a single anomaly-based trading strategy could result in significant loss with non-trivial probability.

Exhibit 1
Descriptive Statistics for Anomaly Portfolios

Anomaly	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Combination
Panel A: Summary Statistics of the Anomaly Returns (long minus short)																
Raw Return (in %)	0.542	0.684	0.549	0.577	0.459	0.528	0.459	0.395	0.285	1.721	0.587	1.217	0.165	0.428	0.727	0.625
	(1.92)	(2.81)	(3.42)	(2.52)	(3.23)	(3.23)	(1.24)	(2.44)	(1.19)	(6.18)	(3.22)	(8.77)	(0.6)	(1.11)	(2.24)	(5.94)
Sharpe Ratio	0.024	0.061	0.047	0.037	0.016	0.031	0.006	–0.005	–0.028	0.227	0.042	0.269	–0.043	0.002	0.052	0.101
3-Factor Alpha (in %)	**1.056**	**1.203**	**0.631**	**0.666**	**0.487**	**0.587**	**0.756**	**0.621**	–0.044	**2.226**	**0.549**	**1.310**	**0.779**	**1.012**	0.145	**0.799**
	(4.39)	(6.86)	(4.54)	(3.62)	(3.38)	(3.29)	(2.17)	(4.05)	–(0.23)	(9.21)	(2.97)	(8.72)	(3.63)	(3.68)	(0.58)	(10.46)
β-MKT	–0.364	–0.222	–0.133	–0.310	0.018	0.033	–0.407	–0.185	–0.069	–0.249	–0.068	–0.105	–0.433	–0.587	0.154	–0.195
	–(6.26)	–(5.22)	–(3.3)	–(5.33)	(0.58)	(0.74)	–(3.34)	–(4.62)	–(1.09)	–(2.79)	–(1.4)	–(1.83)	–(7.8)	–(5.68)	(1.67)	–(6.73)
β-SMB	–0.774	–0.995	–0.164	–0.277	–0.003	0.066	0.217	–0.040	0.371	–0.903	0.324	–0.011	–0.975	–1.361	0.384	–0.276
	–(7.22)	–(15.1)	–(2.73)	–(3.)	–(0.05)	(0.88)	(0.77)	–(0.63)	(4.14)	–(5.67)	(3.68)	–(0.16)	–(11.82)	–(9.64)	(3.41)	–(7.77)
β-HML	–0.260	–0.356	0.134	0.538	–0.117	–0.299	–0.337	–0.321	0.839	–0.341	–0.026	–0.085	–0.271	0.435	1.192	0.049
	–(2.41)	–(4.35)	(1.7)	(6.67)	–(1.71)	–(3.55)	–(1.12)	–(3.)	(7.43)	–(2.93)	–(0.21)	–(1.01)	–(2.1)	(2.13)	(7.03)	(0.86)
Shortfall Probability	46.088	43.883	42.615	44.800	43.675	44.404	47.699	45.532	47.491	38.246	44.420	34.213	48.852	47.915	45.195	38.297
Value at Risk	8.537	6.629	4.303	6.690	4.285	5.648	12.631	5.394	7.175	7.746	6.297	3.704	9.263	13.044	9.181	2.830
Panel B: Summary Statistics of the Anomaly Returns (long leg)																
Raw Return (in %)	1.171	1.095	1.236	1.219	1.236	1.343	1.428	1.292	1.203	1.449	1.321	1.692	1.134	0.957	1.679	1.296
	(5.85)	(5.06)	(5.87)	(6.6)	(4.2)	(4.7)	(4.4)	(5.77)	(4.23)	(6.41)	(4.18)	(7.79)	(5.83)	(5.92)	(5.01)	(6.15)
Sharpe Ratio	0.178	0.151	0.185	0.200	0.146	0.153	0.156	0.192	0.141	0.215	0.142	0.274	0.174	0.163	0.194	0.203
3-Factor Alpha (in %)	**0.329**	**0.240**	**0.229**	**0.221**	0.088	**0.423**	**0.356**	**0.416**	–0.039	**0.668**	**0.133**	**0.760**	**0.322**	0.103	0.314	**0.304**
	(3.84)	(4.4)	(2.46)	(2.49)	(0.78)	(3.19)	(1.99)	(3.76)	–(0.26)	(7.98)	(0.85)	(7.75)	(3.45)	(1.15)	(1.4)	(6.76)
β-MKT	0.812	0.947	0.955	0.876	1.149	1.055	1.003	0.863	1.053	0.906	1.107	0.944	0.823	0.680	1.097	0.951
	(26.7)	(70.03)	(31.85)	(32.53)	(45.36)	(32.27)	(19.99)	(26.87)	(25.18)	(40.05)	(28.8)	(29.39)	(28.49)	(26.28)	(12.79)	(74.66)
β-SMB	–0.007	–0.195	–0.151	–0.135	0.121	0.076	0.497	–0.077	0.358	–0.191	0.520	–0.097	–0.327	–0.218	0.183	0.022
	–(0.11)	–(9.51)	–(2.71)	–(3.22)	(2.11)	(1.41)	(4.46)	–(1.63)	(7.04)	–(5.33)	(8.24)	–(2.61)	–(7.17)	–(6.25)	(1.8)	(1.55)
β-HML	–0.190	–0.244	0.173	0.280	0.017	–0.473	–0.255	–0.120	0.291	–0.399	–0.113	–0.085	–0.033	0.270	0.736	–0.011
	–(2.97)	(9.92)	(2.28)	(5.41)	(0.33)	–(7.04)	–(1.76)	–(1.51)	(3.55)	–(8.99)	–(1.09)	–(1.5)	–(0.49)	(4.5)	(5.04)	–(0.36)
Shortfall Probability	39.209	40.448	39.068	38.152	41.323	41.269	41.305	38.917	41.502	38.171	41.851	35.843	39.219	38.761	39.877	38.316
Value at Risk	5.862	6.357	6.087	5.430	8.035	8.671	9.266	6.258	8.013	6.471	9.240	5.983	5.685	4.554	9.088	5.877
Panel C: Summary Statistics of the Anomaly Returns (short-leg)																
Raw Return (in %)	0.629	0.411	0.686	0.641	0.776	0.815	0.969	0.897	0.917	–0.272	0.733	0.476	0.969	0.528	0.952	0.671
	(1.71)	(1.14)	(2.61)	(1.99)	(2.9)	(3.23)	(2.49)	(3.42)	(3.01)	–(0.72)	(2.53)	(2.06)	(2.85)	(1.25)	(3.77)	(2.38)
Sharpe Ratio	0.029	0.000	0.052	0.036	0.067	0.079	0.066	0.097	0.082	–0.091	0.053	0.013	0.079	0.013	0.108	0.046
3-Factor Alpha (in %)	**–0.727**	**–0.963**	**–0.402**	**–0.446**	**–0.399**	**–0.164**	–0.401	**–0.205**	0.005	**–1.558**	**–0.416**	**–0.550**	**–0.457**	**–0.908**	0.169	**–0.496**
	–(3.35)	–(6.01)	–(3.83)	–(3.01)	–(3.63)	–(1.83)	–(1.64)	–(1.76)	(0.05)	–(7.18)	–(3.57)	–(5.49)	–(2.67)	–(3.91)	(2.14)	–(6.89)
β-MKT	1.176	1.169	1.087	1.186	1.131	1.022	1.410	1.048	1.122	1.155	1.175	1.049	1.256	1.267	0.943	1.146
	(25.59)	(30.08)	(33.54)	(26.14)	(46.93)	(41.53)	(15.94)	(34.94)	(32.78)	(14.86)	(32.02)	(32.9)	(30.54)	(14.71)	(43.13)	(46.54)
β-SMB	0.768	0.800	0.013	0.141	0.124	0.010	0.280	–0.037	–0.013	0.712	0.195	–0.086	0.648	1.142	–0.201	0.298
	(7.24)	(13.4)	(0.3)	(1.91)	(2.03)	(0.26)	(1.5)	–(0.65)	–(0.21)	(4.98)	(2.95)	–(2.14)	(9.4)	(9.06)	–(6.26)	(9.29)
β-HML	0.070	0.112	0.038	–0.257	0.134	–0.174	0.082	0.200	–0.548	–0.058	–0.087	0.000	0.238	–0.165	–0.456	–0.060
	(0.86)	(1.52)	(0.93)	–(4.19)	(2.04)	–(3.29)	(0.47)	(3.14)	–(10.36)	–(0.59)	–(1.41)	(0.0)	(2.76)	–(1.03)	–(11.15)	–(1.55)
Shortfall Probability	46.597	47.572	44.783	45.980	44.364	43.686	45.418	42.910	44.054	51.450	45.228	46.236	44.542	47.644	42.420	45.290
Value at Risk	11.484	10.688	7.922	9.805	8.232	7.616	12.881	7.362	9.168	12.566	9.327	7.803	10.649	14.180	7.239	8.652

Note: The Appendix provides the detailed definition of each variable, and Newey–West adjusted t*-statistics are reported in parentheses (Newey and West [1987]).*

However, the combined strategy considerably mitigates the value at risk to only 2.83.

In addition, Panels B and C of Exhibit 1 separately present similar statistics in the long leg and short leg of the anomalies. Among the 15 anomaly-based trading strategies, 10 (12) strategies produce significant risk-adjusted return in the long leg (short leg). The results indicate that the short leg of the combined strategy yields a significant risk-adjusted return of −0.496% a month, with the long position also generating a significant monthly risk-adjusted return of 0.304%. Our findings are in line with those of Stambaugh, Yu, and Yuan

Exhibit 2

Descriptive Statistics for Anomaly Portfolios (1976–1999 and 2000–2013)

Anomaly	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Combination
Panel A: Summary Statistics of the Anomaly Returns (long minus short, 1976–1999)																
Raw Return (in %)	0.927	0.942	0.516	0.418	0.743	0.592	0.682	0.317	0.098	1.960	0.735	1.316	0.309	0.550	0.062	0.684
	(2.89)	(3.55)	(3.03)	(1.61)	(4.04)	(2.94)	(1.77)	(1.57)	(0.38)	(7.06)	(3.07)	(7.81)	(0.97)	(1.43)	(0.21)	(6.82)
Sharpe Ratio	0.072	0.098	–0.016	–0.034	0.066	0.011	0.022	–0.073	–0.116	0.317	0.047	0.283	–0.049	–0.001	–0.108	0.075
3-Factor Alpha (in %)	**1.432**	**1.312**	**0.541**	**0.430**	**0.751**	**0.701**	**0.903**	**0.632**	–0.145	**2.248**	**0.771**	**1.354**	**0.746**	**0.861**	–0.342	**0.813**
	(5.21)	(7.46)	(3.39)	(2.39)	(3.88)	(3.33)	(2.27)	(3.17)	–(0.75)	(8.58)	(2.98)	(7.82)	(2.49)	(2.83)	–(1.8)	(10.44)
β-MKT	–0.295	–0.141	–0.023	–0.133	0.012	–0.047	–0.116	–0.180	–0.019	–0.070	–0.064	–0.045	–0.224	–0.225	0.034	–0.103
	–(4.81)	–(2.98)	–(0.56)	–(2.43)	(0.27)	–(1.15)	–(1.06)	–(4.43)	–(0.36)	–(1.07)	–(0.99)	–(0.94)	–(3.7)	–(3.49)	(0.52)	–(4.11)
β-SMB	–0.883	–1.066	–0.156	–0.386	–0.053	–0.180	–0.184	–0.126	0.300	–0.701	0.203	0.103	–1.016	–1.256	0.436	–0.332
	–(6.05)	–(18.79)	–(2.31)	–(2.87)	–(0.66)	–(2.46)	–(0.92)	–(1.87)	(3.85)	–(6.63)	(1.61)	(1.47)	–(7.75)	–(7.51)	(4.83)	–(7.52)
β-HML	–0.518	–0.301	0.100	0.760	–0.037	–0.180	–0.446	–0.689	0.946	–0.490	–0.102	–0.098	–0.348	0.442	1.386	0.027
	–(3.66)	–(3.4)	(1.21)	(7.05)	–(0.38)	–(1.57)	–(1.8)	–(6.45)	(9.17)	–(3.92)	–(0.5)	–(1.15)	–(1.92)	(2.31)	(14.99)	(0.79)
Shortfall Probability	42.872	40.512	42.142	45.946	39.598	42.625	45.255	46.154	49.010	32.878	42.229	31.185	47.550	46.548	49.456	34.177
Value at Risk	7.559	5.513	3.767	6.342	3.888	4.647	8.725	5.084	6.428	5.312	5.434	3.096	7.972	9.894	7.450	2.076
Panel B: Summary Statistics of the Anomaly Returns (long minus short, 2000–2013)																
Raw Return (in %)	–0.115	0.244	0.606	0.849	–0.025	0.419	0.079	0.528	0.605	1.313	0.335	1.047	–0.082	0.220	1.863	0.533
	–(0.23)	(0.54)	(2.0)	(2.03)	–(0.13)	(1.45)	(0.11)	(1.95)	(1.31)	(2.3)	(1.15)	(4.36)	–(0.16)	(0.28)	(2.83)	(2.43)
Sharpe Ratio	–0.046	0.016	0.128	0.140	–0.064	0.056	–0.008	0.094	0.082	0.153	0.035	0.256	–0.036	0.005	0.218	0.138
3-Factor Alpha (in %)	0.212	**0.880**	**0.609**	**0.825**	0.039	**0.491**	–0.064	**0.505**	0.062	**1.913**	0.114	**1.158**	**0.480**	0.722	**1.242**	**0.624**
	(0.57)	(2.68)	(3.03)	(2.47)	(0.21)	(1.81)	–(0.09)	(2.18)	(0.18)	(5.33)	(0.39)	(4.75)	(1.8)	(1.55)	(2.22)	(5.21)
β-MKT	–0.603	–0.330	–0.315	–0.479	0.049	0.203	–0.919	–0.352	–0.096	–0.593	–0.119	–0.206	–0.794	–1.144	0.450	–0.354
	–(6.51)	–(4.02)	–(5.86)	–(5.07)	(0.92)	(3.08)	–(4.56)	–(4.98)	–(0.7)	–(4.06)	–(1.3)	–(2.37)	–(10.09)	–(8.45)	(2.69)	–(8.86)
β-SMB	–0.512	–0.886	–0.105	–0.152	0.039	0.243	0.841	0.171	0.431	–0.959	0.492	–0.085	–0.791	–1.273	0.164	–0.152
	–(3.34)	–(8.07)	–(1.07)	–(1.19)	(0.41)	(2.86)	(2.44)	(1.91)	(2.51)	–(3.63)	(4.65)	–(0.95)	–(8.33)	–(6.7)	(0.84)	–(3.7)
β-HML	0.125	–0.330	0.262	0.448	–0.187	–0.459	0.105	0.104	0.768	–0.046	0.093	–0.030	0.002	0.723	0.834	0.162
	(1.05)	–(2.4)	(2.74)	(3.76)	–(2.22)	–(3.5)	(0.26)	(0.92)	(3.48)	–(0.27)	(0.67)	–(0.27)	(0.01)	(3.25)	(3.01)	(2.25)
Shortfall Probability	50.758	48.130	43.073	43.120	50.339	46.347	49.708	44.609	45.513	43.054	47.244	38.107	50.482	49.175	40.562	42.122
Value at Risk	10.061	8.312	5.103	7.212	4.867	7.106	17.631	5.880	8.222	11.031	7.628	4.643	11.214	17.284	10.970	3.877

Note: The Appendix provides the detailed definition of each variable, and Newey–West adjusted t*-statistics are reported in parentheses.*

[2012], and Avramov et al. [2013], who showed that the short positions are substantially more profitable than the long positions, possibly due to short-sale constraints.

In the past decade, the U.S. equity market underwent substantial changes, including the introduction of decimalization and increases in active participation of informed institutional investors as well as high-frequency traders. These technological and structural changes have improved the marketwide liquidity and minimized the constraints to arbitrage, and more importantly, attenuated the profitability of anomaly-based trading strategies (e.g., Chordia, Roll, and Subrahmanyam [2011] and Chordia, Subrahmanyam, and Tong [2014]). In addition, McLean and Pontiff [2016] found that the returns to anomaly-based trading strategies decreased substantially after they were reported in the academic literature. To examine the impact of these changes in our sample, we investigate separately the two subperiods: 1976–1999 and 2000–2013. Exhibit 2 reports the results for both subperiods.

Indeed, observe from Panels A and B of Exhibit 2 that only 9 out of 15 anomalies produce significantly positive Fama–French three-factor adjusted returns in the post-2000 period, compared with 13 profitable anomalies prior to 2000. However, the combined strategy remains highly profitable, generating a significant monthly alpha of 0.813% in the pre-2000 period and 0.624% in the post-2000 period. Because the profitability of each individual anomaly is difficult to predict, and moreover, it is time varying, a naively combined strategy that takes equal positions across the 15 anomalies appears to be attractive for practical purposes. Indeed, it is quite remarkable that the combined strategy displays significantly positive risk-adjusted return also in the post-2000 period even when almost half of the individual anomaly payoffs are insignificant. Moreover, it is evident that the combined

Exhibit 3

Momentum in Anomalies

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Panel A: Risk-Adjusted Anomaly Returns (in %) Regressed on Lagged Risk-Adjusted Anomaly Returns															
$R_{i,t-1}$	0.078								0.080	0.082	0.071	0.074	0.061	0.060	0.058
	(3.29)								(3.5)	(3.65)	(2.8)	(2.99)	(2.4)	(2.25)	(2.23)
$R_{i,t-3:t-2}$		0.057							0.060						
		(1.76)							(1.83)						
$R_{i,t-6:t-4}$			0.082							0.092					
			(2.2)							(2.6)					
$R_{i,t-12:t-7}$				0.083							0.109				
				(1.68)							(2.31)				
$R_{i,t-18:t-13}$					0.077							0.103			
					(1.46)							(2.13)			
$R_{i,t-36:t-19}$						0.291							0.326		
						(3.13)							(3.86)		
$R_{i,t-60:t-37}$							0.302							0.283	
							(3.34)							(3.73)	
$R_{i,t-60:t-2}$								0.437							0.476
								(4.26)							(5.07)
Panel B: Anomaly Returns (in %) Regressed on Lagged Anomaly Returns															
$R_{i,t-1}$	0.100								0.106	0.084	0.099	0.097	0.087	0.085	0.084
	(4.25)								(4.57)	(3.8)	(4.26)	(4.07)	(3.35)	(3.49)	(3.29)
$R_{i,t-3:t-2}$		0.029							0.035						
		(0.91)							(1.09)						
$R_{i,t-6:t-4}$			0.033							0.072					
			(0.84)							(2.06)					
$R_{i,t-12:t-7}$				0.127							0.125				
				(2.2)							(2.58)				
$R_{i,t-18:t-13}$					–0.009							0.008			
					–(0.15)							(0.16)			
$R_{i,t-36:t-19}$						0.077							0.162		
						(0.94)							(2.14)		
$R_{i,t-60:t-37}$							0.269							0.146	
							(2.59)							(1.55)	
$R_{i,t-60:t-2}$								0.257							0.351
								(1.97)							(2.99)

strategy mitigates the noise and risk in the individual strategies and considerably limits the downside risk measured by value at risk in both subperiods.

MOMENTUM IN ANOMALIES

We have shown that a naive trading strategy, which equally weights all anomalies, yields stable and superior risk-adjusted returns even during the recent decade when individual anomaly payoffs tend to diminish. In what follows, we propose the implementation of an active momentum strategy among the various anomalies. Starting from Jegadeesh and Titman [1993], the momentum strategy of buying past winner stocks and selling past loser stocks is considered to be one of the most robust anomalies across countries, industries, and asset classes (Rouwenhorst [1998, 1999], Moskowitz and Grinblatt [1999], Chui, Titman, and Wei [2010], and Asness, Moskowitz, and Pedersen [2013]). Here, we examine whether the performance of top (best-performing) and bottom (worst-performing) anomaly portfolios tends to persist in an economically meaningful way.

As a first pass to examine the persistence in anomaly payoff, we run Fama–MacBeth regressions of anomaly return on its lagged values. Exhibit 3 reports the results for various specifications (see Fama and MacBeth [1973]). Panel A focuses on the Fama–French three-factor adjusted returns, while Panel B employs raw returns. Indeed, there is a strong positive autocorrelation of anomaly payoff across different time horizons ranging from one month to five years. Notice that the one-month autocorrelation coefficient is statistically significant among all specifications examined, and therefore our main strategy for trading anomalies, as outlined in the following, focuses on one-month formation and one-month holding periods.

As the profitability of the anomaly-based trading strategies appears to be persistent over time, professional asset managers can actively select a subset of anomalies, in both the long and the short legs of the trade, to further enhance performance. In particular, consider the investment universe consisting of stocks comprising the 15 top (best-performing) and 15 bottom (worst-performing) anomaly portfolios. All the other stocks can be disregarded for the strategy implementation. Based on this universe of individual stocks, we form 6 (2×3) portfolios, including long-leg Winner (WL), long-leg Median (ML), long-leg Loser (LL), short-leg Winner (WS), short-leg Median (MS), and short-leg Loser (LS). To wit, the WL (LS) portfolio consists of stocks in the top (bottom) N anomaly portfolios recording the highest (lowest) past monthly return; LL (WS) portfolio corresponds to investing in N top (bottom) anomaly portfolios recording the lowest (highest) past monthly return; while the ML (MS) portfolio invests in the remaining $15 - 2N$ top (bottom) portfolios. In our experiments, we consider the number of extreme portfolios (N) to be 3, 4, and 5.

The payoff characteristics of the 2×3 portfolios, i.e., long-leg Winner (WL), long-leg Median (ML), long-leg Loser (LL), short-leg Winner (WS), short-leg Median (MS), and short-leg Loser (LS), are described in Exhibit 4. Also displayed are the payoff characteristics of the "WL–LS" portfolio amounting to take long position in the long-leg winner and short position in the short-leg loser portfolios. There are three panels in Exhibit 4 corresponding to $N = 5$ (Panel A), $N = 4$ (Panel B), and $N = 3$ (Panel C).

Observe form Panel A (B and C) of Exhibit 4 that during the entire sample period, the long positions of past outperforming anomalies (WL) continue to outperform in the following month, generating a significant risk-adjusted return of 0.470% (0.489% and 0.513%) per month, while the short positions of past underperforming anomalies (LS) continue to underperform with a significant risk-adjusted return of −0.803% (−0.893% and −0.958%) per month. The active strategy conditioned on past anomaly returns (WL–LS) yields a monthly risk-adjusted return ranging between 1.273% and 1.471%. The investment payoffs indicate a significant 59% to 84% increase compared with the previously described naive strategy, which generates 0.799% per month (Exhibit 1, Panel A). Similarly, the portfolio payoff based on raw returns provides consistent evidence supporting the economically meaningful persistence in anomaly payoffs. In addition, the Sharpe ratio ranges between 0.179 and 0.194 in our proposed momentum strategy, reflecting a tremendous 77% to 92% increase from the naive strategy with a Sharpe ratio of 0.101 (Exhibit 1, Panel A). Finally, our strategy appears to have similar shortfall probability but higher value at risk compared with the naive benchmark.

Exhibit 5 splits our sample into the two subperiods: 1976–1999 and 2000–2013. As expected, our strategy conditioned on past anomaly returns is less profitable in the recent decade. Still, it remains both statistically and economically significant even during this subperiod. For instance, the monthly risk-adjusted return to the strategy based on 5 (4 and 3) extreme anomalies is 1.447% (1.560% and 1.693%) before 2000, while it remains highly significant at 0.774% (0.899% and 0.912%) in the post-2000 period, as presented in Panel A (B and C). Moreover, this active strategy outperforms the naive combined strategy in both subperiods. Recall, for the combined strategy, the Fama–French three-factor adjusted return is 0.813% (Exhibit 2, Panel A) and 0.624% (Exhibit 2, Panel B) in the pre- and post-2000 periods, respectively. Similarly, our strategy provides higher Sharpe ratios in both subperiods. In sum, by identifying the winner and loser anomaly portfolios, our novel trading strategy outperforms a passive unconditional benchmark and generates significant returns on a risk-adjusted basis. Our results are robust to the number of extreme anomalies used to construct the long–short portfolio as well as to different sample periods.

To further establish the robustness of our findings, we consider a wide range of alternative sorting variables estimated from time-series predictive regressions. Specifically, at the end of each month $t - 1$, the predicted anomaly return is computed as the sum of the regression constant and the slope coefficients multiplied by the values of the predictors realized in the same month. The regression coefficients of each anomaly are estimated using a five-year estimation period (month $t - 61$ to $t - 2$). The predictors include the geometric average of anomaly returns in the last five years (Model 1), lagged anomaly return (Model 2), lagged market illiquidity (Model 3), lagged investor sentiment (Model 4), lagged anomaly return and lagged market illiquidity (Model 5), lagged anomaly return and lagged

EXHIBIT 4
Momentum in Anomalies

	Long			Short			
	WL	ML	LL	WS	MS	LS	WL−LS
Panel A: Momentum in Anomalies Using Five Extreme Anomalies							
Raw Return (in %)	1.487	1.336	1.065	0.918	0.690	0.405	1.082
	(6.35)	(6.36)	(4.93)	(2.98)	(2.57)	(1.38)	(6.85)
Sharpe Ratio	0.225	0.212	0.141	0.084	0.051	–0.001	0.179
3-Factor Alpha (in %)	**0.470**	0.370	0.071	–0.243	–0.441	**–0.803**	**1.273**
	(5.29)	(6.06)	(0.83)	–(2.38)	–(5.88)	–(6.61)	(7.62)
β-MKT	0.959	0.940	0.955	1.141	1.132	1.165	–0.207
	(29.48)	(52.86)	(33.11)	(22.64)	(49.93)	(28.74)	–(3.21)
β-SMB	0.097	–0.048	0.018	0.331	0.166	0.397	–0.299
	(1.66)	–(1.33)	(0.52)	(3.66)	(3.17)	(5.32)	–(2.42)
β-HML	–0.009	–0.015	–0.009	–0.096	–0.040	–0.043	0.034
	–(0.13)	–(0.41)	–(0.17)	–(1.26)	–(1.05)	–(0.7)	(0.29)
Shortfall Probability	37.772	37.969	40.882	43.968	44.991	47.359	38.632
Value at Risk	6.365	5.839	6.534	9.026	8.321	9.649	5.077
Panel B: Momentum in Anomalies Using Four Extreme Anomalies							
Raw Return (in %)	1.512	1.312	1.052	0.933	0.719	0.323	1.189
	(6.18)	(6.34)	(4.81)	(2.96)	(2.67)	(1.09)	(7.01)
Sharpe Ratio	0.222	0.209	0.136	0.084	0.056	–0.014	0.193
3-Factor Alpha (in %)	**0.489**	0.337	0.059	–0.235	–0.417	**–0.893**	**1.383**
	(5.18)	(6.3)	(0.62)	–(2.12)	–(5.76)	–(7.1)	(7.78)
β-MKT	0.977	0.937	0.951	1.145	1.131	1.175	–0.199
	(26.25)	(56.33)	(31.41)	(20.44)	(47.39)	(27.46)	–(2.85)
β-SMB	0.088	–0.026	0.042	0.365	0.198	0.407	–0.319
	(1.75)	–(1.25)	(1.11)	(3.3)	(3.83)	(5.35)	–(2.81)
β-HML	–0.017	0.001	–0.025	–0.108	–0.042	–0.042	0.025
	–(0.23)	(0.01)	–(0.44)	–(1.24)	–(1.05)	–(0.68)	(0.21)
Shortfall Probability	38.005	38.020	41.164	44.033	44.788	47.924	38.405
Value at Risk	6.633	5.765	6.697	9.286	8.312	9.899	5.441
Panel C: Momentum in Anomalies Using Three Extreme Anomalies							
Raw Return (in %)	1.545	1.288	1.071	0.962	0.709	0.263	1.282
	(6.13)	(6.19)	(4.79)	(2.97)	(2.6)	(0.87)	(6.76)
Sharpe Ratio	0.222	0.204	0.134	0.087	0.054	–0.023	0.194
3-Factor Alpha (in %)	**0.513**	0.312	0.068	–0.230	–0.430	**–0.958**	**1.471**
	(4.76)	(6.41)	(0.63)	–(1.89)	–(5.93)	–(6.82)	(7.43)
β-MKT	0.972	0.940	0.965	1.161	1.127	1.189	–0.217
	(23.31)	(59.17)	(29.4)	(19.87)	(47.1)	(25.79)	–(2.93)
β-SMB	0.130	–0.025	0.057	0.375	0.242	0.390	–0.260
	(2.36)	–(1.36)	(1.24)	(3.58)	(6.68)	(3.93)	–(1.95)
β-HML	–0.013	–0.003	–0.033	–0.068	–0.062	–0.043	0.030
	–(0.16)	–(0.1)	–(0.5)	–(0.78)	–(1.74)	–(0.53)	(0.21)
Shortfall Probability	38.096	38.199	41.349	43.975	44.896	48.365	38.771
Value at Risk	6.844	5.768	6.988	9.477	8.385	10.286	6.110

Note: The Appendix provides the detailed definition of each variable, and Newey–West adjusted t-statistics are reported in parentheses.

EXHIBIT 5
Momentum in Anomalies (1976–1999 and 2000–2013)

	1976–1999							2000–2013						
	Long			Short				Long			Short			
	WL	ML	LL	WS	MS	LS	WL−LS	WL	ML	LL	WS	MS	LS	WL−LS
Panel A: Momentum in Anomalies Using Five Extreme Anomalies														
Raw Return (in %)	1.829	1.631	1.313	1.215	0.946	0.560	1.270	0.941	0.847	0.670	0.434	0.264	0.160	0.781
	(7.02)	(6.75)	(5.51)	(3.95)	(3.36)	(1.87)	(7.28)	(2.17)	(2.27)	(1.63)	(0.7)	(0.5)	(0.27)	(2.45)
Sharpe Ratio	0.275	0.249	0.171	0.125	0.076	0.000	0.226	0.157	0.154	0.102	0.038	0.017	0.000	0.135
3-Factor Alpha (in %)	**0.508**	0.332	–0.005	–0.198	–0.466	**–0.939**	**1.447**	**0.372**	0.394	0.194	–0.228	–0.281	**–0.402**	**0.774**
	(5.53)	(5.19)	–(0.05)	–(1.9)	–(5.78)	–(7.38)	(8.)	(2.14)	(3.2)	(1.31)	–(1.11)	–(2.07)	–(2.1)	(2.89)
β-MKT	0.971	0.953	0.958	1.063	1.050	1.078	–0.107	0.901	0.911	0.961	1.246	1.238	1.352	–0.451
	(34.08)	(55.73)	(32.24)	(33.56)	(42.94)	(23.86)	–(1.64)	(14.66)	(30.67)	(17.62)	(13.32)	(35.91)	(24.67)	–(4.55)
β-SMB	0.047	–0.047	–0.023	0.232	0.263	0.478	–0.432	0.186	–0.041	0.050	0.398	0.032	0.221	–0.035
	(1.)	–(1.95)	–(0.48)	(4.65)	(7.82)	(6.25)	–(3.96)	(1.9)	–(0.62)	(0.89)	(2.44)	(0.56)	(2.17)	–(0.19)
β-HML	–0.083	–0.053	0.007	–0.136	–0.116	0.043	–0.126	0.091	0.033	–0.025	–0.109	–0.046	–0.233	0.324
	–(1.16)	–(1.61)	(0.11)	–(2.69)	–(3.54)	(0.64)	–(1.08)	(0.93)	(0.59)	–(0.28)	–(0.93)	–(0.84)	–(3.24)	(2.48)
Shortfall Probability	34.615	35.233	38.268	40.823	42.636	45.909	34.347	42.494	42.443	44.633	47.602	48.267	49.106	43.233
Value at Risk	5.774	5.445	5.923	7.397	7.435	8.402	3.912	7.236	6.460	7.493	11.444	9.739	11.566	6.757
Panel B: Momentum in Anomalies Using Four Extreme Anomalies														
Raw Return (in %)	1.879	1.603	1.281	1.219	0.953	0.514	1.365	0.930	0.831	0.688	0.479	0.326	0.022	0.908
	(6.85)	(6.69)	(5.46)	(3.89)	(3.38)	(1.7)	(7.42)	(2.05)	(2.29)	(1.6)	(0.76)	(0.62)	(0.04)	(2.57)
Sharpe Ratio	0.276	0.245	0.164	0.124	0.078	–0.008	0.233	0.149	0.154	0.102	0.042	0.027	–0.019	0.153
3-Factor Alpha (in %)	**0.550**	0.299	–0.031	–0.193	–0.458	**–1.009**	**1.560**	**0.370**	0.352	0.215	–0.199	–0.235	**–0.529**	**0.899**
	(5.2)	(5.3)	–(0.27)	–(1.68)	–(6.06)	–(7.61)	(7.97)	(1.95)	(3.46)	(1.32)	–(0.94)	–(1.79)	–(2.68)	(3.03)
β-MKT	0.981	0.956	0.949	1.061	1.046	1.096	–0.115	0.924	0.897	0.972	1.260	1.243	1.359	–0.435
	(29.75)	(80.69)	(29.89)	(32.11)	(41.64)	(21.1)	–(1.58)	(13.14)	(28.83)	(16.91)	(12.19)	(35.43)	(25.04)	–(3.99)
β-SMB	0.067	–0.046	–0.017	0.231	0.278	0.498	–0.431	0.150	0.007	0.083	0.463	0.074	0.221	–0.071
	(1.2)	–(2.02)	–(0.3)	(4.1)	(7.2)	(5.88)	–(3.57)	(1.88)	(0.19)	(1.42)	(2.38)	(1.3)	(2.3)	–(0.45)
β-HML	–0.103	–0.037	0.008	–0.132	–0.117	0.077	–0.180	0.087	0.056	–0.062	–0.136	–0.050	–0.260	0.347
	–(1.16)	–(1.37)	(0.12)	–(2.35)	–(3.45)	(1.06)	–(1.34)	(0.84)	(1.13)	–(0.6)	–(1.07)	–(0.89)	–(3.71)	(2.57)
Shortfall Probability	34.751	35.362	38.593	40.925	42.550	46.320	34.636	42.835	42.404	44.705	47.452	47.884	49.876	42.597
Value at Risk	6.005	5.419	5.985	7.520	7.392	8.646	4.316	7.541	6.301	7.814	11.859	9.790	11.826	7.091
Panel C: Momentum in Anomalies Using Three Extreme Anomalies														
Raw Return (in %)	1.888	1.604	1.254	1.227	0.960	0.427	1.461	1.011	0.766	0.787	0.549	0.291	0.008	1.003
	(6.77)	(6.66)	(5.27)	(3.73)	(3.41)	(1.4)	(7.33)	(2.11)	(2.11)	(1.74)	(0.84)	(0.54)	(0.01)	(2.49)
Sharpe Ratio	0.273	0.246	0.153	0.122	0.079	–0.023	0.241	0.157	0.140	0.115	0.051	0.021	–0.020	0.152
3-Factor Alpha (in %)	**0.571**	0.297	–0.071	–0.204	–0.448	**–1.122**	**1.693**	**0.431**	0.291	0.297	–0.160	–0.292	**–0.481**	**0.912**
	(4.5)	(5.8)	–(0.54)	–(1.52)	–(6.58)	–(7.8)	(8.18)	(2.)	(3.11)	(1.54)	–(0.68)	–(2.16)	–(2.19)	(2.61)
β-MKT	0.959	0.958	0.970	1.074	1.045	1.107	–0.147	0.935	0.901	0.983	1.269	1.239	1.407	–0.472
	(26.76)	(73.04)	(28.14)	(30.89)	(47.67)	(20.48)	–(2.07)	(11.72)	(31.97)	(15.53)	(11.43)	(31.63)	(24.35)	–(3.9)
β-SMB	0.123	–0.041	–0.041	0.272	0.272	0.533	–0.409	0.178	0.005	0.133	0.450	0.169	0.129	0.049
	(1.7)	–(2.02)	–(0.67)	(4.08)	(7.44)	(5.56)	–(3.01)	(2.07)	(0.14)	(2.24)	(2.33)	(3.36)	(0.99)	(0.26)
β-HML	–0.119	–0.035	0.011	–0.124	–0.121	0.138	–0.258	0.098	0.047	–0.074	–0.072	–0.078	–0.339	0.437
	–(1.15)	–(1.55)	(0.14)	–(1.88)	–(3.74)	(1.65)	–(1.71)	(0.87)	(0.93)	–(0.64)	–(0.56)	–(1.32)	–(4.48)	(2.84)
Shortfall Probability	34.910	35.309	39.126	41.165	42.472	47.004	34.839	42.595	42.958	44.267	47.117	48.144	49.958	42.820
Value at Risk	6.120	5.396	6.218	7.810	7.361	8.914	4.705	7.899	6.331	8.191	11.929	10.004	12.373	8.116

Note: The Appendix provides the detailed definition of each variable, and Newey–West adjusted t*-statistics are reported in parentheses.*

investor sentiment (Model 6), lagged anomaly return, lagged market illiquidity, and lagged investor sentiment (Model 7), cumulative market return in the last two years (Model 8), lagged anomaly return and cumulative market return in the last two years (Model 9), lagged investor sentiment and cumulative market return in the last two years (Model 10), lagged anomaly return, lagged market illiquidity, lagged investor sentiment, and cumulative market return in the last two years (Model 11). The market illiquidity is defined as the value-weighted average of each stock's monthly Amihud [2002] illiquidity (see the Appendix for detailed definition), and investor sentiment is the level of sentiment index obtained from Baker and Wurgler [2006, 2007].[2] The lagged anomaly return, market illiquidity, and investor sentiment are based on past one-month data.

Momentum across anomalies is based on the predicted returns. In particular, the predicted returns of the long-leg and short-leg of the 15 anomalies are independently sorted into three groups, and the average monthly value-weighted holding period (month *t*) returns for the anomaly-based momentum strategy (WL−LS) are reported in Exhibit 6, with Panels A, B, and C using 5, 4, and 3 extreme anomalies in portfolio construction, respectively.

Several findings are worth noting. First, the Fama–French three-factor adjusted return is impressively significant along all model specifications. For instance, it ranges from 1.257% to 1.523% a month in Panel C of Exhibit 6. Second, market state variables, such as investor sentiment, market illiquidity, and market return, further improve the predictability of anomaly payoff. Some combinations of these variables together with lagged anomaly return generate the highest risk-adjusted return in the long–short strategy across all three panels. Third, sorting on predicted anomaly return using lagged anomaly return and market states (1.336% in Panel A, Model 11, Exhibit 6) further outperforms the strategy of sorting on lagged one-month anomaly return (1.273% in Exhibit 4, Panel A) on a risk-adjusted basis.

Exhibit 7 further investigates the subsample results of Exhibit 6, that is, for the periods 1976–1999 and 2000–2013. Our previous findings remain robust in both subperiods, and in particular, investor sentiment (Model 4) has uniformly been the best predictor in the recent decade, generating a considerable risk-adjusted return of between 1.046% and 1.243% a month.

It is well documented that the momentum payoff is time varying. In particular, the momentum-trading strategy is unprofitable following periods of low investor sentiment (Stambaugh, Yu, and Yuan [2012]). In response to such time variation, we examine the momentum in anomalies conditional on investor sentiment. The results are reported in Exhibit 8. The high (low) investor sentiment is recorded when the investor sentiment is above (below) median over the last two years.

The empirical evidence suggests that the cross-sectional return anomalies are more profitable when investor sentiment is high, reflecting binding short-sale constraints following episodes of high sentiment (Stambaugh, Yu, and Yuan [2012] and Antoniou, Doukas, and Subrahmanyam [2013]). More importantly, our strategy, which conditions on past anomaly returns, yields higher risk-adjusted returns following high-sentiment periods and at the same time still produces abnormal performance following low-sentiment periods. For instance, when selecting three extreme anomalies, the monthly Fama–French three-factor adjusted return is 1.732% in high-sentiment periods, compared with 1.182% when investor sentiment is low.

CONCLUSION

This article employs a set of 15 well-documented market anomalies and investigates the persistence in anomaly payoff. We find a strong positive autocorrelation in anomaly payoff across different time horizons. We then propose an active anomaly-based trading strategy that considers the stocks comprising the top (best-performing, long-leg) and bottom (worst-performing, short-leg) anomaly portfolios. Among the 15 top and 15 bottom portfolios, they are independently sorted into loser and winner groups according to the lagged one-month returns. Our strategy takes a long position in the long-leg winner and a short position in the short-leg loser portfolios and yields a significantly positive monthly risk-adjusted return ranging between 1.273% and 1.471%, indicating a 59% to 84% increase, compared with a passive, naive benchmark that equally invests in all 15 anomalies. This active strategy also remains profitable with monthly risk-adjusted return ranging from 0.774% to 0.912% in the post-2000 period, despite the poor performance in individual anomalies.

EXHIBIT 6
Predicted Momentum in Anomalies

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Panel A: Predicted Momentum in Anomalies Using Five Extreme Anomalies											
Raw Return (in %)	0.949	1.056	1.040	1.192	1.030	1.210	1.166	1.039	1.114	1.159	1.184
	(4.83)	(5.93)	(5.87)	(5.85)	(5.72)	(6.68)	(6.17)	(5.62)	(6.51)	(5.92)	(6.49)
Sharpe Ratio	0.146	0.201	0.186	0.199	0.198	0.223	0.215	0.192	0.227	0.207	0.224
3-Factor Alpha (in %)	**1.175**	**1.255**	**1.163**	**1.327**	**1.196**	**1.324**	**1.264**	**1.207**	**1.283**	**1.298**	**1.336**
	(7.42)	(7.76)	(7.36)	(6.97)	(7.83)	(7.89)	(7.53)	(6.96)	(8.33)	(7.48)	(8.38)
β-MKT	–0.207	–0.203	–0.146	–0.180	–0.200	–0.206	–0.189	–0.178	–0.209	–0.221	–0.241
	(–4.68)	–(4.7)	–(3.88)	–(2.66)	–(5.22)	–(3.61)	–(3.7)	–(4.01)	–(4.79)	–(4.15)	–(4.66)
β-SMB	–0.557	–0.373	–0.406	–0.516	–0.402	–0.336	–0.359	–0.396	–0.337	–0.379	–0.240
	–(6.81)	–(5.17)	–(3.99)	–(5.64)	–(4.72)	–(4.28)	–(4.11)	–(4.32)	–(4.36)	–(3.96)	–(1.77)
β-HML	–0.080	–0.084	0.038	0.098	0.002	0.120	0.146	–0.032	–0.013	0.094	0.037
	–(0.74)	–(1.1)	(0.34)	(0.75)	(0.03)	(1.02)	(1.32)	–(0.31)	–(0.17)	(0.71)	(0.28)
Shortfall Probability	39.803	37.023	37.881	38.005	37.053	36.724	36.932	37.473	35.889	37.370	36.544
Value at Risk	5.092	4.188	4.502	5.230	4.096	4.657	4.582	4.314	3.956	4.760	4.478
Panel B: Predicted Momentum in Anomalies Using Four Extreme Anomalies											
Raw Return (in %)	1.063	1.176	1.086	1.315	1.101	1.349	1.293	1.111	1.213	1.170	1.297
	(5.06)	(6.28)	(5.56)	(6.03)	(5.97)	(7.02)	(6.66)	(5.6)	(6.72)	(5.57)	(6.33)
Sharpe Ratio	0.164	0.222	0.181	0.213	0.213	0.242	0.237	0.205	0.243	0.197	0.235
3-Factor Alpha (in %)	**1.275**	**1.370**	**1.219**	**1.432**	**1.285**	**1.456**	**1.375**	**1.277**	**1.385**	**1.297**	**1.420**
	(7.32)	(7.99)	(6.92)	(6.93)	(8.13)	(8.21)	(8.05)	(7.1)	(8.35)	(6.78)	(7.64)
β-MKT	–0.203	–0.192	–0.135	–0.163	–0.175	–0.189	–0.165	–0.157	–0.200	–0.200	–0.225
	–(4.18)	–(4.11)	–(3.2)	–(2.24)	–(4.34)	–(3.04)	–(2.94)	–(3.82)	–(4.29)	–(3.51)	–(3.73)
β-SMB	–0.570	–0.366	–0.476	–0.587	–0.433	–0.326	–0.381	–0.454	–0.359	–0.450	–0.185
	–(5.77)	–(4.21)	–(4.78)	–(5.54)	–(4.47)	–(3.5)	–(4.13)	–(5.07)	–(4.05)	–(4.76)	–(1.16)
β-HML	–0.046	–0.089	0.025	0.144	–0.065	0.112	0.160	–0.037	–0.026	0.120	0.069
	–(0.39)	–(0.97)	(0.21)	(1.02)	–(0.79)	(0.88)	(1.3)	–(0.36)	–(0.27)	(0.93)	(0.46)
Shortfall Probability	39.435	36.590	38.514	37.816	36.656	36.331	36.382	37.210	35.599	38.001	36.513
Value at Risk	5.461	4.468	5.033	5.656	4.210	4.998	4.813	4.490	4.191	5.130	4.890
Panel C: Predicted Momentum in Anomalies Using Three Extreme Anomalies											
Raw Return (in %)	1.152	1.174	1.299	1.430	1.117	1.435	1.335	1.213	1.366	1.250	1.334
	(4.96)	(5.88)	(6.51)	(6.29)	(5.7)	(7.06)	(6.82)	(5.58)	(6.66)	(5.49)	(5.94)
Sharpe Ratio	0.181	0.198	0.237	0.221	0.204	0.236	0.229	0.218	0.265	0.199	0.214
3-Factor Alpha (in %)	**1.351**	**1.362**	**1.412**	**1.518**	**1.257**	**1.518**	**1.383**	**1.363**	**1.523**	**1.341**	**1.412**
	(6.96)	(7.72)	(7.85)	(6.83)	(7.36)	(8.2)	(8.01)	(7.08)	(8.)	(6.16)	(6.59)
β-MKT	–0.185	–0.180	–0.108	–0.122	–0.112	–0.177	–0.122	–0.138	–0.164	–0.177	–0.199
	–(3.93)	–(3.4)	–(2.31)	–(1.49)	–(2.74)	–(2.64)	–(2.07)	–(3.17)	–(3.48)	–(2.7)	–(2.96)
β-SMB	–0.619	–0.438	–0.460	–0.594	–0.463	–0.325	–0.393	–0.513	–0.415	–0.458	–0.165
	–(6.9)	–(4.57)	–(4.08)	–(4.67)	–(5.64)	–(3.02)	–(3.77)	–(5.67)	–(4.36)	–(4.25)	–(0.9)
β-HML	–0.021	–0.067	0.031	0.163	–0.028	0.152	0.193	–0.002	–0.018	0.183	0.139
	–(0.17)	–(0.7)	(0.24)	(1.06)	–(0.35)	(1.03)	(1.38)	–(0.02)	–(0.18)	(1.28)	(0.79)
Shortfall Probability	38.850	37.960	36.415	37.778	37.323	37.013	37.018	37.062	35.199	38.329	37.819
Value at Risk	5.538	5.126	4.853	6.127	4.568	5.686	5.294	4.828	4.546	5.678	5.739

Note: The Appendix provides the detailed definition of each variable, and Newey–West adjusted t*-statistics are reported in parentheses.*

Exhibit 7

Predicted Momentum in Anomalies (subperiods)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Panel A: Predicted Momentum in Anomalies Using Five Extreme Anomalies											
Panel A1: 1976–1999											
Raw Return (in %)	1.263	1.388	1.221	1.175	1.210	1.194	1.256	1.313	1.377	1.288	1.314
	(5.46)	(6.64)	(5.4)	(5.16)	(5.61)	(5.55)	(5.81)	(5.65)	(6.67)	(5.82)	(6.39)
Sharpe Ratio	0.221	0.282	0.211	0.199	0.225	0.213	0.233	0.239	0.282	0.237	0.252
3-Factor Alpha (in %)	**1.443**	**1.590**	**1.355**	**1.338**	**1.367**	**1.369**	**1.403**	**1.494**	**1.579**	**1.461**	**1.480**
	(8.74)	(9.02)	(7.69)	(7.67)	(8.15)	(7.59)	(8.33)	(8.97)	(9.46)	(9.32)	(8.92)
Shortfall Probability	29.886	32.328	35.351	35.782	34.316	34.972	34.230	34.314	32.239	34.233	33.569
Value at Risk	3.756	3.590	4.122	4.130	3.719	3.891	3.831	4.034	3.537	3.928	3.781
Panel A2: 2000–2013											
Raw Return (in %)	0.434	0.510	0.745	1.258	0.769	1.249	1.041	0.604	0.737	0.973	0.936
	(1.3)	(1.67)	(2.73)	(3.24)	(2.59)	(3.75)	(3.04)	(1.55)	(2.07)	(2.51)	(2.55)
Sharpe Ratio	0.054	0.090	0.151	0.216	0.173	0.243	0.204	0.096	0.142	0.170	0.175
3-Factor Alpha (in %)	0.409	**0.421**	**0.574**	**1.046**	**0.670**	**0.933**	**0.736**	0.308	**0.496**	**0.636**	**0.659**
	(1.64)	(1.65)	(2.48)	(2.98)	(2.86)	(3.16)	(2.45)	(0.98)	(1.85)	(1.86)	(2.1)
Shortfall Probability	36.025	44.024	41.727	39.796	40.689	38.544	39.978	44.244	42.190	41.463	41.155
Value at Risk	5.246	5.067	5.123	6.744	4.600	5.804	5.704	6.254	5.413	6.446	5.948
Panel B: Predicted Momentum in Anomalies Using Four Extreme Anomalies											
Panel B1: 1976–1999											
Raw Return (in %)	1.408	1.521	1.309	1.297	1.370	1.412	1.399	1.446	1.503	1.360	1.404
	(5.66)	(6.7)	(5.29)	(5.33)	(6.08)	(6.29)	(6.22)	(5.89)	(6.91)	(5.61)	(6.45)
Sharpe Ratio	0.244	0.298	0.224	0.223	0.258	0.269	0.266	0.269	0.299	0.243	0.267
3-Factor Alpha (in %)	**1.566**	**1.724**	**1.431**	**1.438**	**1.528**	**1.594**	**1.554**	**1.606**	**1.709**	**1.540**	**1.558**
	(8.77)	(8.89)	(7.33)	(8.01)	(8.98)	(8.23)	(9.05)	(9.02)	(10.03)	(9.13)	(8.67)
Shortfall Probability	29.319	32.299	35.234	35.246	33.625	33.238	33.326	33.457	32.126	34.430	33.302
Value at Risk	3.886	3.927	4.371	4.338	3.961	3.946	3.942	4.119	3.822	4.223	3.946
Panel B2: 2000–2013											
Raw Return (in %)	0.511	0.602	0.723	1.392	0.669	1.267	1.134	0.617	0.792	0.987	0.814
	(1.47)	(1.96)	(2.44)	(3.43)	(2.27)	(3.47)	(3.2)	(1.58)	(2.02)	(2.24)	(2.01)
Sharpe Ratio	0.068	0.111	0.125	0.221	0.147	0.224	0.211	0.095	0.148	0.157	0.135
3-Factor Alpha (in %)	0.377	**0.481**	**0.607**	**1.173**	**0.629**	**0.911**	**0.790**	0.313	**0.541**	0.612	0.455
	(1.44)	(1.83)	(2.13)	(2.97)	(2.5)	(2.68)	(2.43)	(0.97)	(1.79)	(1.53)	(1.26)
Shortfall Probability	37.028	43.299	43.057	39.754	41.623	39.449	39.853	44.311	42.058	42.162	42.852
Value at Risk	6.050	5.268	6.079	7.424	4.530	6.521	6.120	6.475	5.707	7.226	6.619
Panel C: Predicted Momentum in Anomalies Using Three Extreme Anomalies											
Panel C1: 1976–1999											
Raw Return (in %)	1.466	1.446	1.476	1.402	1.457	1.418	1.449	1.513	1.715	1.439	1.451
	(5.45)	(6.15)	(5.66)	(5.52)	(6.32)	(6.12)	(6.34)	(5.58)	(7.18)	(5.74)	(6.15)
Sharpe Ratio	0.249	0.256	0.266	0.238	0.272	0.248	0.265	0.268	0.336	0.253	0.257
3-Factor Alpha (in %)	**1.658**	**1.649**	**1.551**	**1.545**	**1.577**	**1.605**	**1.591**	**1.653**	**1.897**	**1.593**	**1.605**
	(8.71)	(8.73)	(7.54)	(8.39)	(8.47)	(7.93)	(9.32)	(8.5)	(10.38)	(8.75)	(7.77)
Shortfall Probability	29.563	34.241	33.806	35.046	33.360	34.550	33.734	33.897	31.279	34.332	34.193
Value at Risk	4.144	4.414	4.337	4.603	4.115	4.449	4.228	4.480	4.067	4.428	4.409

(continued)

EXHIBIT 7 *(continued)*
Predicted Momentum in Anomalies (subperiods)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Panel C2: 2000–2013											
Raw Return (in %)	0.646	0.745	1.008	1.519	0.577	1.497	1.178	0.926	1.124	0.942	0.808
	(1.7)	(2.17)	(3.39)	(3.54)	(1.81)	(3.71)	(3.31)	(2.27)	(2.89)	(2.05)	(1.95)
Sharpe Ratio	0.097	0.128	0.197	0.223	0.106	0.239	0.200	0.155	0.211	0.136	0.120
3-Factor Alpha (in %)	**0.512**	**0.610**	**0.862**	**1.243**	**0.568**	**1.045**	**0.772**	0.557	**0.821**	0.502	0.395
	(1.76)	(2.05)	(3.28)	(2.77)	(1.85)	(2.89)	(2.01)	(1.63)	(2.45)	(1.09)	(1.02)
Shortfall Probability	36.166	42.985	40.241	39.821	43.438	39.106	40.450	42.109	39.815	43.100	43.602
Value at Risk	6.307	6.191	5.700	8.165	5.166	7.408	6.839	6.722	6.039	7.969	7.439

Note: The Appendix provides the detailed definition of each variable, and Newey–West adjusted t*-statistics are reported in parentheses.*

EXHIBIT 8
Momentum in Anomalies and Investor Sentiment

	High Investor Sentiment				Low Investor Sentiment			
Anomaly	Raw Return	*t*-Stats	3-Factor Alpha	*t*-Stats	Raw Return	*t*-Stats	3-Factor Alpha	*t*-Stats
1	1.207	(2.99)	1.455	(3.87)	–0.201	–(0.47)	0.524	(1.51)
2	1.203	(3.5)	1.542	(5.93)	0.159	(0.44)	0.856	(3.61)
3	0.962	(4.09)	0.841	(3.95)	0.042	(0.21)	0.225	(1.17)
4	1.158	(3.51)	0.908	(3.41)	–0.099	–(0.37)	0.295	(1.22)
5	0.594	(2.8)	0.682	(3.32)	0.304	(1.56)	0.232	(1.13)
6	0.501	(2.13)	0.696	(2.61)	0.596	(2.25)	0.520	(1.97)
7	0.714	(1.45)	0.902	(1.7)	0.180	(0.28)	0.652	(1.21)
8	0.456	(1.96)	0.568	(2.39)	0.356	(1.45)	0.585	(2.66)
9	0.625	(1.74)	0.155	(0.63)	–0.029	–(0.1)	–0.235	–(0.91)
10	2.258	(5.4)	2.595	(7.02)	1.188	(3.07)	1.847	(5.97)
11	0.458	(1.57)	0.517	(1.69)	0.771	(3.28)	0.677	(2.65)
12	1.318	(6.38)	1.357	(6.13)	1.047	(5.43)	1.170	(5.83)
13	0.623	(1.46)	0.876	(2.54)	–0.378	–(0.97)	0.477	(1.65)
14	1.268	(2.26)	0.915	(2.25)	–0.559	–(0.95)	0.779	(2.07)
15	0.680	(1.61)	0.029	(0.08)	0.878	(1.61)	0.189	(0.44)
WL–LS 5	1.342	(5.64)	1.421	(5.31)	0.868	(3.86)	1.094	(4.77)
WL–LS 4	1.449	(5.71)	1.551	(5.56)	0.961	(3.85)	1.157	(4.71)
WL–LS 3	1.613	(5.87)	1.732	(5.7)	1.012	(3.49)	1.182	(4.14)

Note: The Appendix provides the detailed definition of each variable, and Newey–West adjusted t*-statistics are reported in parentheses.*

Furthermore, our findings are robust to alternative sorting variables estimated from time series predictive regressions conditional on market states and appear to be stronger following periods of high investor sentiment. Overall, this study extends the literature on price momentum by implementing momentum to a broad set of market anomalies, and our findings have important implications for the practice of asset management.

APPENDIX

VARIABLE DEFINITIONS

Variables	Definitions
A. Anomaly Measures	
Failure Probability	Failure probability in a given month t is computed as follows: $\text{Distress}_{i,t} = -9.164 - 20.264 \times \overline{NIMTA}_{i,t} + 1.416 \times TLMTA_{i,t} - 7.129 \times \overline{EXRET}_{i,t} + 1.411 \times SIGMA_{i,t} - 0.045 \times RSIZE_{i,t} - 2.132 \times CASHMTA_{i,t} + 0.075 \times MB_{i,t} - 0.058 \times PRICE_{i,t}$, where $TLMTA_{i,t}$ is the ratio of total liabilities (Compustat quarterly item LTQ) divided by the sum of market equity and total liabilities of stock i in month t, $SIGMA_{i,t}$ is the annualized three-month rolling sample standard deviation, $RSIZE_{i,t}$ is the logarithm of the ratio of the stock market equity to that of the S&P 500 Index, $CASHMTA_{i,t}$ is the ratio of cash and short-term investments (item CHEQ) divided by the sum of market equity and total liabilities, $MB_{i,t}$ is the market-to-book ratio, $PRICE_{i,t}$ is the logarithm of the price per share and truncated above at 15 USD. $\overline{NIMTA}_{i,t}$ and $\overline{EXRET}_{i,t}$ are further computed as follows: $\overline{NIMTA}_{i,t} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{i,t-3:t-1} + \ldots + \phi^9 NIMTA_{i,t-12:t-10})$, $\overline{EXRET}_{i,t} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{i,t-1} + \ldots + \phi^{11} EXRET_{i,t-12})$, $EXRET_{i,t} = \log(1 + R_{i,t}) - \log(1 + R_{S\&P\,500,t})$, where $\phi = 2^{-1/3}$, $\text{NIMTA}_{i,t-3:t-1}$ is the ratio of net income (item NIQ) divided by the sum of market equity and total liabilities, $R_{i,t}$ is the return of stock i in month t, and $R_{\text{S\&P500},t}$ is the return of S&P500 index, following Campbell, Hilscher, and Szilagyi [2008] and Chen, Novy-Marx, and Zhang [2011].
O-Score	O-score in a given quarter q is computed as follows: $OScore_{i,q} = -1.32 - 0.407 \times \log(ADJASSET_{i,q}/CPI_q) + 6.03 \times TLTA_{i,q} - 1.43 \times WCTA_{i,q} + 0.076 \times CLCA_{i,q} - 1.72 \times OENEG_{i,q} - 2.37 \times NITA_{i,q} - 1.83 \times FUTL_{i,q} + 0.285 \times INTWO_{i,q} - 0.521 \times CHIN_{i,q}$, where $ADJASSET_{i,q}$ is the adjusted total assets of stock i in quarter q, defined as total assets (Compustat quarterly item ATQ) plus 10% of the difference between market equity and book equity, CPI_q is the consumer price index, $TLTA_{i,q}$ is the leverage ratio defined as the book value of debt (item DLCQ plus item DLTTQ) divided by $ADJASSET_{i,q}$, $WCTA_{i,q}$ is the ratio of working capital (item ACTQ − item LCTQ) divided by $ADJASSET_{i,q}$, $CLCA_{i,q}$ is the ratio of current liabilities (item LCTQ) divided by current assets (item ACTQ), $OENEG_{i,q}$ is a dummy variable taking a value of one if total liabilities (item LTQ) exceeds total assets and zero otherwise, $NITA_{i,q}$ is the ratio of net income (item NIQ) divided by $ADJASSET_{i,q}$, $FUTL_{i,q}$ is the ratio of fund provided by operations (item PIQ) divided by total liabilities, and $INTWO_{i,q}$ is a dummy variable taking a value of one if net income is negative for the last two quarters and zero otherwise. $CHIN_{i,q}$ is further computed as follows: $CHIN_{i,q} = (NI_{i,q} - NI_{i,q-1})/(\lvert NI_{i,q}\rvert + \lvert NI_{i,q-1}\rvert)$, where $NI_{i,q}$ is the net income of stock i in quarter q, following Ohlson [1980] and Chen, Novy-Marx, and Zhang [2011].
Net Stock Issuance	Net stock issuance in a given year t is computed as follows: $NetStk_{i,t} = \log(SHROUT_{i,t}/SHROUT_{i,t-1})$, where $SHROUT_{i,t}$ is the split-adjusted number of shares outstanding of stock i in year t.
Composite Equity Issuance	Composite equity issuance in a given year t is computed as follows: $CompEqu_{i,t} = \log(ME_{i,t}/ME_{i,t-5}) - LR_{i,t-5:t}$, where $ME_{i,t}$ is the market equity of stock i in year t, $LR_{i,t-5:t}$ is the cumulative log return on stock i over the previous five years, following Daniel and Titman [2006].
Total Accruals	Total accruals in a given year t is computed as follows: $Accruals_{i,t} = [(\Delta CA_{i,t} - \Delta Cash_{i,t}) - (\Delta CL_{i,t} - \Delta STD_{i,t} - \Delta TP_{i,t}) - Dep_{i,t}]/\overline{ASSET}_{i,t}$, where $\Delta CA_{i,t}$ is the change in current assets (COMPUSTAT annual item ACT) of stock i in year t, $\Delta Cash_{i,t}$ is the change in cash and short-term investments (item CHE), $\Delta CL_{i,t}$ is the change in current liabilities (item LCT), $\Delta STD_{i,t}$ is the change in debt included in current liabilities (item DLC), $\Delta TP_{i,t}$ is the change in income taxes payable (item TXP), $Dep_{i,t}$ is the depreciation and amortization expense (item DP), and $\overline{ASSET}_{i,t}$ is the average total assets (item AT) of the beginning and end of year t, following Sloan [1996].

(continued)

Variables	Definitions
Net Operating Assets	Net operating assets in a given year t is computed as follows: $NOA_{i,t} = [(ASSET_{i,t} - Cash_{i,t}) - (ASSET_{i,t} - STD_{i,t} - LTD_{i,t} - MI_{i,t} - PS_{i,t} - CE_{i,t})]/ASSET_{i,t-1}$, where $ASSET_{i,t}$ is the total assets (Compustat annual item AT) of stock i in year t, $Cash_{i,t}$ is the cash and short-term investments (item CHE), $STD_{i,t}$ is the debt included in current liabilities (item DLC), $LTD_{i,t}$ is the long term debt (item DLTT), $MI_{i,t}$ is the minority interests (item MIB), $PS_{i,t}$ is the preferred stocks (item PSTK), and $CE_{i,t}$ is the common equity (item CEQ), following Hirshleifer, Hou, Teoh, and Zhang [2004].
Momentum	Formation period return in a given month m is computed as the cumulative six-month return from month $m - 6$ to month $m - 1$, following Jegadeesh and Titman [1993].
Gross Profitability	Gross profitability in a given year t is computed as follows: $GP_{i,t} = (REVT_{i,t} - COGS_{i,t})/ASSET_{i,t}$, where $REVT_{i,t}$ is the total revenue (Compustat annual item REVT) of stock i in year t, $COGS_{i,t}$ is the cost of goods sold (item COGS), $ASSET_{i,t}$ is the total assets (item AT), following Novy-Marx [2013].
Asset Growth	Asset growth in a given year t is computed as follows: $ASSETG_{i,t} = (ASSET_{i,t} - ASSET_{i,t-1})/ASSET_{i,t-1}$, where $ASSET_{i,t}$ is the total assets (COMPUSTAT annual item AT) of stock i in year t, following Cooper, Gulen, and Schill [2008].
Return on Assets	Return on assets in a given quarter q is computed as follows: $ROA_{i,q} = INCOME_{i,q}/ASSET_{i,q-1}$, where $INCOME_{i,q}$ is the income before extraordinary items (COMPUSTAT quarterly item IBQ) of stock i in quarter q, and $ASSET_{i,q-1}$ is the total assets (item ATQ).
Abnormal Capital Investment	Abnormal capital investment in a given year t is computed as follows: $CI_{i,t} = \frac{CE_{i,t}}{(CE_{i,t-1} + CE_{i,t-2} + CE_{i,t-3})/3} - 1$, where $CE_{i,t}$ is the ratio of capital expenditures (COMPUSTAT annual item CAPX) divided by sales (item SALE) of stock i in year t, following Titman, Wei, and Xie [2004].
SUE	Standardized unexpected earnings (SUE) in a given quarter q is computed as follows: $SUE_{i,q} = \frac{e_{i,q} - e_{i,q-4}}{\sigma_{it}}$, where $e_{i,q}$ is the most recent quarterly earnings per share for stock i announced in quarter q, $e_{i,q-4}$ is the earnings per share announced four quarters ago, and $\sigma_{i,q}$ is the standard deviation of unexpected earnings ($e_{i,q} - e_{i,q-4}$) over the previous eight quarters (quarter $q - 8$ to $q - 1$), following Chan, Jegadeesh, and Lakonishok [1996].
Analyst Dispersion	Analyst dispersion in a given month m is computed as the standard deviation of analysts' earnings per share forecasts for the upcoming fiscal year-end, standardized by the absolute value of the mean forecast in the same month, following Diether, Malloy, and Scherbina [2002].
Idiosyncratic Volatility	The idiosyncratic volatility in a given month m is computed as follows: $IdioVol_{i,m} = \sum_{d\in m} R^2_{i,d,m} - \sum_{d\in m} MKT^2_{d,m}$, where $R_{i,d,m}$ is the return of stock i in day d of month m, $MKT_{d,m}$ is return on the value-weighted CRSP index, following Campbell et al. [2001], and Avramov et al. [2013].
Book-to-Market	The book-to-market ratio in a given quarter q is computed as: $BM_{i,q} = BE_{i,q}/ME_{i,q}$, where $BE_{i,q}$ refers to the book value of equity of stock i in quarter q, computed as the summation of stockholders' equity and deferred taxes, minus the preferred stock, and $ME_{i,q}$ refers to its market value at the end of the same quarter.
B. Stock Market Measure	
Market Illiquidity	The market illiquidity is defined as the value-weighted average of each stock's monthly Amihud illiquidity, and the Amihud illiquidity in a given month m is computed as follows: $ILLIQ_{i,m} = \left[\sum_{d=1}^{n} \lvert R_{i,d}\rvert/(P_{i,d} \times N_{i,d})\right]/n$, where n is the number of trading days in each month m, $\lvert R_{i,d}\rvert$ is the absolute value of return of stock i on day d, $P_{i,d}$ is the daily closing price of stock i, and $N_{i,d}$ is the number of shares of stock i traded during day d, following Amihud [2002].

ENDNOTES

[1]We thank Kenneth French for making the common factor returns available at hi website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2]We thank Jeffrey Wurgler for making their index of investor sentiment publicly available. The models requiring investor sentiment end in 2010 due to data availability.

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