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The supraview of return predictive signals

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Abstract This study seeks to inform investment academics and practitioners by describing and analyzing the population of return predictive signals (RPS) publicly identified over the 40-year period 1970–2010. Our supraview brings to light new facts about RPS, including that more than 330 signals have been reported; the properties of newly discovered RPS are stable over time; and RPS with higher mean returns have larger standard deviations of returns and also higher Sharpe ratios. Using a sample of 39 readily programmed RPS, we estimate that the average cross-correlation of RPS returns is close to zero and that the average correlation between RPS returns and the market is reliably negative. Abstracting from implementation costs, this implies that portfolios of RPS either on their own or in combination with the market will tend to have quite high Sharpe ratios. For academics who seek to document that they have found a genuinely new RPS, we show that the probability that a randomly chosen RPS has a positive alpha after being orthogonalized against five (25) other randomly chosen RPS is 62 % (32 %), suggesting that the returns of a potentially new RPS need to be orthogonalized against the returns of some but not all pre-existing RPS. Finally, we posit that our findings pose a challenge to investment academics in that they imply that either US stock markets are pervasively inefficient, or there exist a much larger number of rationally priced sources of risk in equity returns than previously thought.

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1 Introduction

In this paper, we seek to inform investment academics and practitioners by reporting the results of taking the supra or "forest-level" view of the firm-specific characteristics that accounting, finance, and other business faculty have identified over the past 40 years as being predictive (usually of the cross-section) of US stock returns. We refer to such characteristics as return predictive signals, or RPS for short.

Prior scholarly research into RPS has centered on discovering and publishing the identity and return properties of new signals, typically in the form of one RPS per paper. In contrast to this approach, we take the supraview of the population of RPS and bring to light several new facts about RPS that enrich and challenge academic understanding and that may provide practitioners with information they can use to improve their investment performance.

We approximate the population of RPS by compiling a database of the RPS published in academic business journals or disclosed in academic working papers over the period 1970–2010. The first result we highlight from this database is that there are far more RPS than has heretofore been appreciated. Our approximation of the population of RPS identifies more than 330 different signals—four times the number used by McLean and Pontiff (2012), more than six times the number listed by Subrahmanyam (2010), and vastly beyond the classic size, book-to-market, momentum, and beta firm characteristics or factor returns. However, despite the abundance of publicly documented RPS, we observe that 88 % of RPS papers only orthogonalize the returns of the particular signal they focus on against one or more of SMB/size, HML/book-to-market, and MOM/momentum.

Second, we statistically describe the return properties of RPS as reported in the original scholarly papers. We document that the mean annualized equally weighted return, standard deviation of annualized equally weighted returns, and annualized Sharpe ratio based on equally weighted returns across all RPS in our database (where available in or calculable from the underlying published or working paper) are 12.1 %, 12.1 %, and 1.04, respectively ($n = 239$). The mean annualized value-weighted return, standard deviation of annualized value-weighted returns, and annualized Sharpe ratio based on value-weighted returns are 8.1 %, 12.2 %, and 0.70, respectively ($n = 98$). We also find that RPS returns outperform the US equity market in that the annual excess returns and Sharpe ratios on the CRSP equally weighted (value-weighted) market over the equivalent time periods are 9.5 % and 0.50 (6.6 % and 0.44), respectively.

Third, we document that the return performance of heavily cited RPS such as accruals and momentum is worse than that of the median RPS. For example, the accruals signal in Sloan (1996) has a mean annual equally weighted return of 10.4 % and a Sharpe ratio of 0.81, whereas the median accounting-based RPS has a mean annual equally weighted return of 12.0 % and a Sharpe ratio of 0.91. Likewise, Jegadeesh and Titman's (1993) momentum signal (defined as 6-month lagged returns with a holding period of 6 months) has a mean equally weighted annualized return of 11.4 % and a Sharpe ratio of 0.61, yet the median finance-based RPS has a mean equally weighted annualized return of 11.9 % and a Sharpe ratio of 0.98.

The fourth new fact we report is that the mean returns, standard deviations of returns, and Sharpe ratios of newly discovered RPS remain stable over time: RPS discovered in the 2000s have similar return properties to those discovered in the 1990s, 1980s, and 1970s. This suggests that the predominantly academic process of RPS discovery is independent of the investment potential of RPS and/or that the technologies and data used by academics to discover new RPS have improved over time to offset a shrinking pool of high performing but not yet discovered RPS.

Fifth, we show that although RPS with higher mean returns are riskier in the sense that they have larger time-series standard deviations of returns, they also exhibit higher Sharpe ratios. We find the latter result to be surprising because we expect the correlation between returns and Sharpe ratios to be zero or negative. If the risk of an RPS is fully captured by the standard deviation of its returns over time, then in a rational market where an increase in expected return is accompanied by a commensurately higher degree of risk, Sharpe ratios should be equal for all RPS. A positive correlation between RPS mean returns and Sharpe ratios suggests that either the market is inefficient or the standard deviation of returns is an incomplete proxy for RPS risk.

Sixth, we contrast the performance of the population of RPS with the performance of the signals whose use practitioners publicly disclose by reporting the mean returns and Sharpe ratios of the RPS that J.P. Morgan disclosed that it made available to its clients for the construction of their investment portfolios (*US Factor Reference Book,* Jan. 27, 2011). We find that the RPS disclosed by J.P Morgan have a maximum Sharpe ratio of 1.1 and appear to be truncated at that level, regardless of whether implementation of the RPS is restricted to large-cap, mid-cap, or small-cap firms. In contrast, the maximum Sharpe ratio for academically discovered and reported RPS is 3.1, and of all equally weighted (value-weighted) academic RPS, 36 % (14 %) have Sharpe ratios that exceed 1.1.

Seeking to contribute to financial practice, we also explore the investment performance that may be available to practitioners who can exploit large numbers of RPS, especially at low implementation cost. We do so by means of the analytical machinery of Bailey and López de Prado (2012), who show that the Sharpe ratio of an equal-volatility-weighted portfolio is compactly described by just three parameters: the number and mean Sharpe ratio of the assets in the portfolio and the average signed cross-correlation between the assets' returns.

As a first step toward measuring all of the more than 55,000 return cross-correlations present in our database of more than 330 RPS and the Sharpe ratios of all portfolios that can be created from the population of RPS, we take a sample of 39 RPS that are straightforward to program from CRSP, Compustat, and I/B/E/S and for which data are available during the period January 1985–December 2011. We observe that the average cross-correlation among the 39 equally weighted (value-weighted) time-series of RPS monthly returns is just 0.05 (0.05), suggesting that practitioners may be able to markedly improve their investment performance by exploiting large numbers of RPS. We analytically confirm this within the Bailey and López de Prado setup by showing that abstracting from direct transactions and other implementation costs, an average cross-correlation of 0.05 means that an equal-volatility-weighted portfolio of 3 (30; 300) RPS will have an expected annualized Sharpe ratio that is an impressive 1.65 (3.50; 4.33) times the mean Sharpe ratio of its component RPS.

When we empirically apply Bailey and López de Prado's equal-volatility-weighted portfolio approach to a randomly chosen set of 3 (30) RPS from our sample of 39 signals, we observe average annualized portfolio Sharpe ratios of 1.21 and 0.59 (2.43 and 1.22) for equally weighted and value-weighted returns, respectively, as compared to 0.75 and 0.37 for a single randomly chosen RPS. While large, such multi-RPS portfolio Sharpe ratios point to the indirect implementation costs that practitioners may face when seeking to exploit multiple RPS, because the average empirical Sharpe ratios are approximately 30 % smaller than would be expected based on the Sharpe ratios documented in or calculable from the original RPS papers. The dilution in RPS portfolio Sharpe ratios likely occurs because our estimation of the cross-correlations between RPS returns, like that of practitioners, uses data from both before and after the RPS were publicly first disclosed.

We next explore the implications of the cross-correlations of RPS returns for the inferential robustness of academic research into newly discovered RPS. We do so by estimating the average absolute cross-correlation in RPS returns, noting that the lower the average absolute cross-correlation, the more independent and distinct each RPS is from every other RPS. We observe that the average absolute cross-correlation between RPS returns in our sample of 39 signals is 0.29 for equal-weighted returns and 0.22 for value-weighted returns. To calibrate the implications of such correlations for academic inferences, using our sample of 39 RPS we empirically estimate that the probability that any given signal in the population of RPS will have a reliably positive alpha after being orthogonalized against five (10, 15, 25) other randomly chosen RPS is 62 % (50 %, 40 %, 32 %). We infer from this result that an academic who uncovers what she hypothesizes is a new RPS reasonably needs to orthogonalize the returns of the new RPS against the returns from some but not every single pre-existing RPS to arrive at a statistically robust inference as to the true novelty of the RPS.

Finally, returning to the supraview perspective that motivates and drives our paper, we posit that a unified model of market efficiency or inefficiency will need to be able to accommodate the new facts that we document about RPS—particularly the large number of RPS that exist and their generally uncorrelated return structure. We conjecture that to do this will be somewhat challenging, because the existence of more than 330 RPS whose returns are not highly cross-correlated prima facie suggests that either US stock markets are pervasively inefficient or that the number of rationally priced sources of risk in equity returns that theorists must understand and explain is far larger than previously envisaged. In terms of future work, we propose that identifying the number and economic features of the subset of RPS that span the returns generated by the full set of more than 330 individual RPS is likely to be a necessary condition for both theorists and empiricists to make progress in better understanding the nature of market efficiency and inefficiency.

The remainder of our study proceeds as follows. In Sect. 2 we describe the construction of our RPS database, and in Sect. 3 we report and in places seek to explain the new findings that emerge from our analysis of this database. In Sect. 4 we theoretically and empirically estimate the investment performance that might be able to be extracted by practitioners from the population of RPS that have been discovered and publicly reported by academic and practitioner researchers. We conclude our paper in Sect. 5.

2 RPS database

We construct our approximation of the population of RPS discovered and publicly disclosed by primarily accounting, finance, and other business faculty by searching top-tier US accounting, finance, and practitioner journals for RPS papers published between January 1970 and December 2010. References in these papers on occasion led us to papers published in lower-tier journals, which were then included in the database. We also searched for RPS working papers on SSRN as of Dec. 31, 2010, focusing on the FEN Capital Markets: Market Efficiency, FEN Capital Markets: Asset Pricing & Valuation, and ARN Financial Accounting Subject Matter eJournals. We coded into the database only the first paper on an RPS.[1]

We categorize each RPS as accounting-based, finance-based, or other-based. An accounting-based RPS is one for which the signal is in the firm's financial statements (e.g., accruals, cash flows, assets). A finance-based RPS is one for which the signal was directly or indirectly dependent on the firm's stock price (e.g., return momentum, implied skewness in returns derived from option prices). The exceptions to these rules are that P/E is classified as an accounting signal, book-to-market is classified as a finance signal, and any accounting signal interacted with a finance signal is classified as a finance signal.[2] Other-based signals are those that are neither accounting- nor finance-related, such as labor mobility, stock repurchases, or a stock's ticker symbol.

The full list of the attributes we recorded in each RPS paper is detailed in the Appendix, although not every paper contains information on every attribute. Among the most important attributes are those pertaining to the authors (e.g., whether their area of expertise is in accounting, finance, etc.), the date the papers were published (if published by Dec. 31, 2010), the date of the first publicly available version of the

[1] There is a vast academic literature on accounting and finance anomalies, well summarized by survey papers such as Lev and Ohlson (1982), Bernard (1989), Kothari (2001), Keim and Ziemba (2000), Barberis and Thaler (2003), Schwert (2003), and Subrahmanyam (2010). However, these surveys do not seek to identify and gather together the full population of RPS, nor statistically describe the return properties of the RPS population.

[2] There are relatively few signals (just five) that explicitly combine an accounting data item and a finance data item into a composite signal. Our results are not sensitive to the reclassification of accounting signals interacted with finance signals as accounting signals instead of finance signals.

papers (typically on SSRN, and if not on SSRN, defined to be 2 years prior to the date of publication), the databases on which the studies drew (CRSP, Compustat, etc.), the name and definition of the signals, the period over which the signals were analyzed, whether the returns from the signals were computed on an equally weighted or value-weighted basis, the firm characteristics or factor returns against which the signal returns were orthogonalized, and key aspects of signal performance—most notably the annualized mean returns and annualized Sharpe ratios.

3 New insights into RPS made visible by taking the supraview

Our RPS database enables us to measure and report several new supralevel ("forest-level") facts about RPS that we believe may be of value to academics and practitioners. In this section we describe these new RPS facts and seek to begin to understand them.

3.1 The number of RPS

Our RPS database contains 333 different signals that were first publicly reported over the period 1970–2010 by accounting, finance, or other business scholars. The complete 17-page bibliography of the papers underlying these signals is available on request from the authors.

We argue that our identification of more than 330 RPS constitutes evidence that far more RPS exist than is commonly presumed. The number of RPS we identify is four times the number listed by McLean and Pontiff (2012), more than six times the 50 finance-based RPS reported by Subrahmanyam (2010), and vastly more than the four classic firm characteristics of firm size, book-to-market, momentum and beta, or their factor returns HML, SMB, MOM and RMKT that are conventionally seen as the way to risk-adjust returns. Of the 333 RPS in our database, 147 are accounting-based, 106 are finance-based, and 78 are other-based.

In Fig. 1 we graph the cumulative number of RPS discovered and publicly reported by business academics. Figure 1 indicates that the discovery of RPS has grown exponentially over time, and at least as of December 2010, has shown no signs of abating.

3.2 Authorship of RPS papers and the journals in which RPS papers are published

Table 1 contains descriptive statistics about the authors of RPS papers and the journals in which RPS papers have been published. Panel A shows that accounting faculty dominate in the discovery of accounting-based RPS, comprising 56 % of the authorship of accounting-based RPS papers, while finance faculty dominate in the discovery of finance-based RPS and other-based RPS papers, making up 79 % and 75 % of the authorship of such papers, respectively. The relative density of sole versus joint authorship on RPS papers is similar across accounting-based, finance-based, and

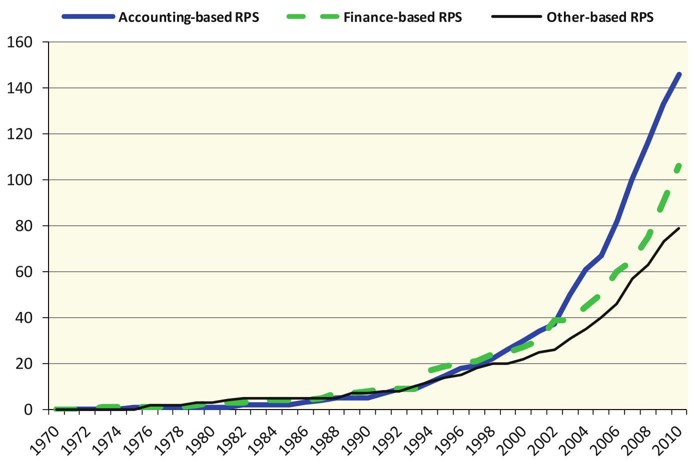


Fig. 1 Cumulative number of return predictive signals (RPS) discovered and publicly reported by accounting, finance, and other business academics, 1970–2010

other-based signals, with 20 % of RPS papers being sole-authored, 38 % written by two authors, 34 % by three authors, and 9 % by four or more authors.

Of the RPS papers in our database, 47 % were unpublished as of Dec. 31, 2010. Of those that were published, 23 % appeared in the top academic accounting journals (which we define as *The Accounting Review*, *Journal of Accounting Research*, *Journal of Accounting & Economics*, *Review of Accounting Studies*, *Contemporary Accounting Research*), while 49 % were published in the top academic finance journals (*Journal of Finance*, *Journal of Financial Economics*, *Review of Financial Studies*, *Journal of Financial & Quantitative Analysis*), and 13 % came out in top practitioner finance journals (*Financial Analysts Journal*, *Journal of Futures Markets*). A variety of other journals published the remaining 13 % of papers (e.g., *Journal of Accounting, Auditing & Public Policy*, *Journal of Banking & Finance*, *The Financial Review*, *Management Science*, *Journal of Wealth Management*).

3.3 Databases used in RPS papers and sample restrictions applied in RPS papers

Regardless of the signal studied, 99 % of RPS papers use CRSP stock returns and 74 % employ the Compustat database (Table 2). One reason for the intense use of Compustat is that, beyond accounting-based RPS papers, a large number of finance-based and other-based papers orthogonalize returns against book-to-market and calculate firms' book values from Compustat data. Beyond CRSP and Compustat, 24 % of papers use analyst forecasts (typically of earnings) from I/B/E/S, 7 % use CDA Spectrum or Thomson Reuters Insider Filings, 4 % use OptionMetrics, 3 % use SDC, and 1 % use the SEC. Likely reflecting the ingenuity of researchers in the hunt for new RPS, 37 % of RPS papers draw on nontraditional databases such as the NBER patent database, Google searches, ExecuComp, Moody's, and Dow Jones News Retrieval.

Table 1 Descriptive statistics regarding the authors of return predictive signal (RPS) papers and the journals in which RPS papers have been published, 1970–2010

Panel A: *RPS author area of expertise*

Author area of expertise	Type of RPS					
	Accounting		Finance		Other	
Accounting	191	56 %	33	13 %	25	14 %
Finance	120	35 %	198	79 %	133	75 %
Economics	12	4 %	0	0 %	7	4 %
Law	1	<1 %	0	0 %	1	1 %
Practitioner	19	6 %	21	8 %	11	6 %
	343	100 %	252	100 %	177	100 %

Panel B: *Number of authors per RPS paper*

Number of authors	Type of RPS		
	Accounting	Finance	Other
One	26	23	17
Two	61	36	28
Three	49	35	30
Four or more	12	13	3
	148	107	78

Panel C: *Journals in which RPS papers have been published*

Journal	Type of RPS		
	Accounting	Finance	Other
The accounting review	10	0	0
Contemporary accounting research	9	0	2
Journal of accounting research	8	0	0
Journal of accounting and economics	7	0	1
Review of accounting studies	2	0	0
Journal of accounting, auditing and finance	1	0	1
Journal of finance	15	24	12
Journal of financial economics	3	9	8
Review of financial studies	0	4	4
Journal of financial and quantitative analysis	1	3	4
Journal of futures markets	0	5	1
Financial analysts journal	9	4	4
Other	10	8	8
Unpublished working paper @ Dec. 31, 2010	73	50	34

Table 2 Descriptive statistics on the databases used in return predictive signal (RPS) papers and the sample restrictions applied in RPS papers, 1970–2010

Panel A: Databases used in RPS papers

Database	All papers (%)	Type of RPS		
		Accounting (%)	Finance (%)	Other (%)
CRSP	99	99	98	100
Compustat	74	91	58	66
I/B/E/S	24	32	22	13
CDA Spectrum/Thomson	7	4	4	17
OptionMetrics	4	0	13	0
First call	3	2	6	0
SDC	3	2	0	8
SEC	1	2	0	1
All other databases	36	25	33	62

Panel B: Sample restrictions applied in RPS papers

Sample restrictions	All papers (%)	Accounting (%)	Finance (%)	Other (%)
Only allow Dec. 31 FYEs	4	8	0	0
Financial firms excluded	25	44	5	0

We note that RPS papers typically apply few sample restrictions. The main restriction is that 44 % of accounting-based RPS papers exclude financial firms out of a concern that the financial statements of such entities—especially the nature and properties of their accruals—are very different from those of nonfinancial entities.

3.4 RPS returns

This subsection describes the diversity of returns reported in RPS papers. We explain how we standardize this diversity to create annualized returns that we then use in calculating the first comprehensive, population-based descriptive statistics of RPS returns. We also use the annualized returns to compare returns across different types of RPS and across calendar time.

3.4.1 Returns measurement in RPS papers

RPS papers use one of three methods to identify new signals that predict (usually the cross-section of) future stock returns: regressions, event studies, and hedge portfolios. Of these three methods, only event studies and hedge portfolios yield point estimates of the mean returns that an investor could (on paper) earn by exploiting the signal, because regression studies typically focus on the hypothesis-testing-oriented question of whether the signal is efficiently priced by the market. In contrast, most event studies and virtually all hedge portfolio papers are focused on estimating the returns that could (in theory, abstracting from transactions costs) be earned by trading on the signal.

In the regression approach, the researcher includes his or her publicly available signal of interest X_{it} for firm *i* measured at time *t* as a firm-specific explanatory variable in a regression of firm-specific returns earned beyond time *t* on X_{it} and a variety of controls. The regression is typically pooled time-series cross-sectional and aims to determine whether the estimated coefficient on X_{it} is nonzero and therefore inconsistent with conventional definitions of market efficiency. The main design choices facing the researcher in the regression approach are the variables included as risk or controls and the length of the holding period of the dependent return variable.

The event study approach harks back to the days when such methods were popular in testing market efficiency and researchers studied the behavior of mean returns after a particular firm event was first publicly reported, looking for post-event-announcement drift. In this approach, RPS returns are created by effectively taking long-only or short-only (but not long/short) positions at the announcement of a particular event Y with a view to using any post-event-announcement mean stock price drift to test whether investors efficiently price the stock of firm *i* at *t* when it announces Y. For example, assume that $Y_{it} =$ the announcement by firm *i* at time *t* that it will undertake a seasoned equity offering. If the researcher hypothesizes that firm *i*'s stock price will underreact to such an announcement, then a short position in firm *i*'s stock could conceptually be taken at *t*. The firm characteristic underpinning the RPS is the fact that firm *i* has announced at *t* that it is undertaking a seasoned equity offering, a situation that clearly varies across both firms and time. In this long-only or short-only position approach, the main design choices facing the researcher are the length of time leading up to the announcement used to parameterize a model of expected returns in the post-announcement period, the risk factors used in the model of expected returns, and the length of time the stock is held after Y is announced.

In contrast, in the long/short dollar-neutral portfolio approach the researcher is interested in the pricing of firm characteristics that are amenable to being used in real-time trading strategies on large numbers of firms. The long/short method has largely superseded the event study and regression approaches over the past 20 years, and it works as follows. Suppose that the researcher hypothesizes that low (high) values of firm characteristic *Z*—e.g., accruals—at time *t* indicate that the firm is temporarily undervalued (overvalued) relative to other firms. To capitalize on this, the researcher calculates *Z* for each firm at time *t*, sorts firms based on Z_{it}, and in a dollar-neutral manner goes long (short) in a group of firms with the lowest (highest) values of *Z*. The long/short hedge portfolio is then held between time *t* and time $t + k$, at which point positions are liquidated, *Z* is recalculated, and new long/short positions are taken. After orthogonalizing the raw returns against a set of risk factors, the researcher obtains a time-series of RPS mean returns. There are four main design choices facing the researcher in the long/short dollar-neutral portfolio approach: how firms are grouped by the firm characteristic *Z*, how long the stock is held after long/short positions are taken, the length of time the strategy is implemented, and the risk factors against which the raw returns are orthogonalized.

In Table 3 we report the returns-related design choices that have been made by RPS researchers. Panel A indicates that the mean length of time used in implementing RPS is 305 months, or just over 25 years. Accounting-based RPS use an average of 23 years of data, as compared to 30 years in finance-based RPS, most likely because accounting-based RPS often require data from firms' statements of cash flow, and these only became available in a high-quality, machine-readable form in 1987 with the passing of SFAS No. 95. When grouping firms based on signal sorts, 38 % of the studies group firms into deciles or something akin to deciles, while 31 % group firms based on quintiles, tertiles, or above/below the median value (panel B). A majority (57 %) of other-based RPS use no grouping because they use the event-study or long- or short-only position approach. We observe in panel C that the most common frequencies with which RPS as a whole are calculated are monthly (56 %) and annually (26 %). Only 7 % of RPS papers sort the underlying signal and take new investment positions on a daily or weekly basis.

Most striking, however, is the evidence in panel D showing that of the 91 % of RPS papers that do orthogonalize their raw RPS returns against at least one risk factor or firm-specific characteristic, just 12 % orthogonalize against something other than one or more of RMKT/beta, SMB/size, HML/book-to-market, and MOM/momentum. While surprising given the plethora of documented RPS, the 12 % figure is similar to the responses from both practitioner and academic respondents to the survey sent by Richardson et al. (2010, Table 1, Q1). In answer to the question "Which risk model is most appropriate for risk calibration of an equity trading strategy?" a maximum of 23 % of practitioners and 19 % of academics indicated they used a model other than one that included RMKT/beta, SMB/size, HML/book-to-market, or MOM/momentum.

3.4.2 Standardization of returns computation methods in RPS papers

Since return holding periods vary from 1 day to 1 year in RPS studies (Table 3, panel C), we standardize reported mean returns by annualizing. We do this by multiplying daily mean returns by 250, weekly mean returns by 52, monthly mean returns by 12, quarterly mean returns by 4, and semiannual mean returns by 2. Since surprisingly few RPS papers report Sharpe ratios, for RPS papers in which a time-series of mean RPS returns is reported we typically extract the annualized Sharpe ratio from the *t*-statistic on the mean return (where reported) and the number of return periods used in calculating the mean return.[3]

3.4.3 Documentation of the return performance of the population of RPS

For the first time in the RPS literature, the supraview nature of our RPS database enables us to describe the return properties of the population of RPS that have been discovered and publicly reported by academics. We document a variety of new facts and insights about RPS returns, several of which we believe are surprising and intriguing.

In our description of the return properties of RPS, we separate out equally weighted returns (Table 4) from value-weighted returns (Table 5). Tables 4 and 5 each display a set of key statistics across five different panels, namely all types of RPS pooled together (panel A), accounting-based RPS only (panel B), finance-based RPS only (panel C), other-based RPS only (panel D), and the excess returns on the

[3] We therefore set aside a goodly number of *t*-statistics that are not based on a time-series of mean RPS returns, because the Sharpe ratio is only properly defined for a time-series of returns.

Table 3 Descriptive statistics on measurement of returns reported in RPS papers, 1970–2010

Panel A: Number of months of data used in RPS analyses

No. sample months	All papers	Type of RPS		
		Accounting	Finance	Other
Min.	12	13	36	12
Mean	305	279	359	291
Max.	1,008	648	1,008	939

Panel B: Method of grouping RPS into portfolios

Portfolio grouping	All papers (%)	Type of RPS		
		Accounting (%)	Finance (%)	Other (%)
<10 %	8	9	9	6
10 %–19 %	38	53	29	18
20 %–50 %	31	28	44	20
Other or no grouping	23	10	19	57

Panel C: Frequency with which RPS is recalculated, new positions taken and held

Signal recalculated	All papers (%)	Type of RPS		
		Accounting (%)	Finance (%)	Other (%)
Daily	4	3	5	4
Weekly	3	0	7	2
Monthly	56	41	74	60
Quarterly	10	14	7	6
Semiannually	1	3	1	0
Annually	26	40	5	28

Panel D: Risk characteristics [or factor returns] used to orthogonalize RPS returns

	All papers (%)	Type of RPS		
		Accounting (%)	Finance (%)	Other (%)
Beta [RMKT]	70	63	74	79
Firm size [SMB]	77	86	67	73
Book-to-market [HML]	66	68	63	69
Momentum [MOM]	45	40	48	56
Other	12	7	17	13
None	9	5	15	8

market over the same time periods and using the same return holding periods as the full set of RPS in the database (panel E).

Since RPS returns as calculated by academics are zero-net-investment, we subtract the 1-month risk-free rate from market returns in arriving at the statistics

Table 4 Statistics on the annualized equally weighted returns earned in RPS papers and the excess equally weighted market returns over the same intervals as the RPS, 1970–2010

	Mean	SD	Sharpe
Panel A: All types of RPS			
Min.	0.8 %	4.3 %	0.08
25th percentile	6.6 %	8.6 %	0.68
Median	10.8 %	11.0 %	0.87
Mean	12.2 %	12.1 %	1.04
75th percentile	16.1 %	14.3 %	1.29
Max.	35.0 %	31.2 %	2.98
SD	7.1 %	5.2 %	0.55
Skewness	0.9	1.3	1.0
Number of RPS	237	208	208
Panel B: Accounting-based RPS			
Min.	3.3 %	4.6 %	0.37
25th percentile	8.5 %	9.2 %	0.72
Median	12.0 %	11.5 %	0.91
Mean	13.2 %	12.4 %	1.10
75th percentile	17.4 %	16.7 %	1.38
Max.	32.4 %	31.2 %	2.50
SD	6.9 %	4.9 %	0.97
Skewness	0.9	1.2	0.9
Number of RPS	115	97	97
Panel C: Finance-based RPS			
Min.	3.7 %	4.8 %	0.35
25th percentile	6.6 %	9.4 %	0.61
Median	11.9 %	11.8 %	0.98
Mean	13.5 %	12.6 %	1.11
75th percentile	16.9 %	14.4 %	1.30
Max.	35.0 %	30.9 %	2.98
SD	7.6 %	5.0 %	0.63
Skewness	0.8	1.3	1.1
Number of RPS	72	68	68
Panel D: Other-based RPS			
Min.	0.8 %	4.8 %	0.35
25th percentile	4.3 %	6.8 %	0.52
Median	6.4 %	9.0 %	0.75
Mean	8.1 %	10.6 %	0.81
75th percentile	10.6 %	11.5 %	1.05
Max.	22.8 %	30.8 %	1.97
SD	5.4 %	6.2 %	0.44
Skewness	1.2	1.9	0.7
Number of RPS	50	43	43

Table 4 continued

	Mean	SD	Sharpe
Panel E: Equally weighted market returns over the same RPS intervals (all types of RPS)			
Min.	−5.0 %	10.7 %	−0.29
25th percentile	8.5 %	18.3 %	0.44
Median	9.3 %	19.3 %	0.49
Mean	9.5 %	19.1 %	0.50
75th percentile	11.2 %	19.9 %	0.59
Max.	24.8 %	30.3 %	1.37
SD	2.6 %	1.8 %	0.15
Skewness	−0.4	−0.3	0.5
Number of RPS	333	333	333

reported in panel E. On a pre–transactions cost, pre-fees basis, panel E therefore enables us to compare the naïve baseline investing approach of going long in the RPS versus going long in the market.[4] Inspection of panel A in Tables 4 and 5 reveals the following noteworthy results.

3.5 New facts that emerge from adopting the supraview of RPS

3.5.1 Number of RPS and weighting methods used in RPS

Of the 333 papers in our RPS database, 84 do not report a mean return. This usually occurs because the RPS is identified using the cross-sectional regression approach (see Sect. 3.4.1). Of the 249 papers that do report a mean RPS return, 237 report equally weighted returns, 99 report value-weighted returns, and 87 report both equally weighted and value-weighted returns. This implies that academics view equally weighted returns as the default metric for RPS returns, almost always reporting only value-weighted returns in addition to, not instead of, equally weighted returns.

3.5.2 Mean RPS returns

Consistent with the proposition that market efficiency operates at the post–transactions cost, not pre–transactions cost level, we find that across all types of RPS taken together, the mean annualized equally weighted RPS return of 12.2 % is 4.1 % higher than the mean annualized value-weighted RPS return of 8.1 % (Table 4, panel A and Table 5, panel A). We note that the mean equally weighted

[4] The two investing approaches are naïve because RPS returns and excess market returns will be less than perfectly positively correlated. Hence a linear combination of the two approaches would dominate either one separately.

Table 5 Statistics on the annualized value-weighted returns earned in RPS papers and the excess value-weighted market returns over the same intervals as the RPS, 1970–2010

	Mean	SD	Sharpe
Panel A: All types of RPS			
Min.	−2.4 %	3.9 %	−0.21
25th percentile	3.5 %	8.6 %	0.34
Median	7.1 %	11.0 %	0.61
Mean	8.1 %	12.2 %	0.70
75th percentile	10.9 %	15.2 %	0.84
Max.	35.0 %	27.9 %	3.09
SD	6.3 %	5.0 %	0.58
Skewness	1.4	1.0	2.1
Number of RPS	99	87	87
Panel B: Accounting-based RPS			
Min.	−1.4 %	4.6 %	−0.11
25th percentile	4.2 %	8.8 %	0.41
Median	7.1 %	11.0 %	0.67
Mean	8.0 %	12.2 %	0.63
75th percentile	10.6 %	13.8 %	0.83
Max.	30.1 %	27.3 %	1.47
SD	5.3 %	4.9 %	0.31
Skewness	2.0	1.5	0.0
Number of RPS	35	27	27
Panel C: Finance-based RPS			
Min.	−0.8 %	7.2 %	0.14
25th percentile	3.6 %	9.5 %	0.34
Median	9.7 %	13.7 %	0.69
Mean	10.4 %	13.8 %	0.69
75th percentile	14.4 %	15.4 %	1.10
Max.	35.0 %	27.9 %	3.03
SD	7.1 %	4.8 %	0.63
Skewness	1.1	0.7	1.7
Number of RPS	42	39	39
Panel D: Other-based RPS			
Min.	−2.4 %	5.0 %	−0.21
25th percentile	1.7 %	7.3 %	0.21
Median	3.7 %	9.2 %	0.50
Mean	4.4 %	10.2 %	0.45
75th percentile	6.2 %	11.9 %	0.68
Max.	15.5 %	21.5 %	1.30
SD	4.1 %	4.4 %	0.36
Skewness	0.8	1.3	0.2
Number of RPS	23	22	22

Table 5 continued

	Mean	SD	Sharpe
Panel E: Value-weighted market returns over the same RPS intervals (all types of RPS)			
Min.	−8.6 %	6.6 %	−0.44
25th percentile	5.5 %	15.0 %	0.35
Median	6.6 %	15.4 %	0.43
Mean	6.6 %	15.3 %	0.44
75th percentile	8.3 %	15.8 %	0.55
Max.	15.0 %	21.7 %	1.49
SD	2.4 %	1.3 %	0.18
Skewness	−1.2	−2.3	0.6
Number of RPS	333	333	333

return of 12.2 % is very close to the stylized “ideal hedge fund” return of 1 % per month. We also note that the 4.1 % larger mean return earned by equally weighted RPS may explain why researchers seldom report value-weighted returns in RPS papers. All else held equal, the larger the mean RPS return, the more impressive the underlying signal looks and the more likely the associated *t*-statistic is to exceed 2.0 and thus assist in rendering the paper publishable. Consistent with this idea, the mean standard deviation of equally weighted RPS returns (12.2 % per Table 4, panel A) is virtually identical to that of value-weighted RPS returns (12.1 % per Table 5, panel A).[5]

The statistical distributions of the returns to accounting-based RPS are similar to those of finance-based RPS, conditional on a given return weighting scheme (Table 4, panels B and C; Table 5, panels B and C). However, other-based RPS display markedly lower mean returns and lower Sharpe ratios than accounting-based and finance-based RPS (Tables 4 and 5, panel D).

3.5.3 RPS Sharpe ratios

The next finding we highlight is that the mean annualized Sharpe ratio across all types of equally weighted RPS returns is 1.04 (Table 4, panel A), as compared to 0.70 for value-weighted RPS returns (Table 5, panel A). In contrast, the mean Sharpe ratios on the equally and value-weighted markets over the same time periods as the underlying RPS are 0.50 and 0.44, respectively. The combination of higher mean returns and higher Sharpe ratios indicates that on a pre–transactions cost basis, RPS more often than not yield superior performance relative to the market. Indeed, in untabulated analysis we find that 88 % (63 %) of RPS have a higher Sharpe ratio than the equally weighted (value-weighted) market, and 50 % (39 %) have both a higher mean return and a lower return variance.

[5] In untabulated analysis we find that the mean *t*-statistic associated with equally weighted returns is 5.0, as compared to the mean *t*-statistic of 3.7 associated with value-weighted returns.

3.5.4 Returns of heavily cited RPS relative to those of median-performing RPS

We also document the surprising result that the mean returns and Sharpe ratios earned by heavily cited RPS such as the post–earnings announcement drift, accruals, firm size, and momentum are below those of the median RPS.[6] For example, Sloan's accruals factor has a mean annual equally weighted return of 10.4 % and a Sharpe ratio of 0.81, and Jegadeesh and Titman's momentum factor (signal = 6-month lagged returns, holding period = 6 months) has a mean annual equally weighted return of 11.4 % and a Sharpe ratio of 0.61. These compare to a median equally weighted RPS return of 10.8 % and a median equally weighted RPS Sharpe ratio of 0.87 (Table 4, panel A).[7]

3.5.5 Temporal evolution of the properties of RPS returns

When we analyze RPS in calendar time based on the year of the first actual or inferred working paper pertaining to a particular RPS, we find that the mean returns and Sharpe ratios of newly discovered RPS do not materially change over time.[8] Expressed differently, RPS discovered in the decade from 2001 through 2010 do not have materially higher or lower returns or Sharpe ratios relative to RPS discovered in the 1990s, 1980s, or 1970s.

We illustrate this in panels a and b of Fig. 2, where we plot the mean RPS returns reported by the paper that first discovered an RPS against the year in which the paper was made publicly available. Equally weighted (value-weighted) mean returns are denoted by green circles (red squares). All types of newly discovered RPS combined are shown in panel A, while just accounting-based RPS are shown in panel B. Beneath each panel we report the *t*-statistics on the estimated slope coefficients in regressions of mean annualized equally weighted and value-weighted RPS returns on the year in which the RPS was first reported. None of the *t*-statistics is significant at the 5 % level in a two-tailed test, confirming the visual indication that there are no reliable trends over calendar time in the mean returns of newly discovered RPS. A similar lack of trending over time is apparent in panels c and d of Fig. 2, where we plot the annualized standard deviations of equally weighted and value-weighted mean RPS returns by the year in which the paper that first discovered the RPS was made publicly available. The absence of time trends is also observed in Fig. 3, in which we plot the Sharpe ratios of annualized equally

[6] Using Google Scholar as of Sept. 17, 2012, it is the case that Jegadeesh and Titman's (1993) momentum signal is the most heavily cited RPS; Banz's (1981) firm size signal is the third most heavily cited RPS; Sloan's (1996) accruals signal is the seventh most heavily cited RPS; and Ball and Brown's (1968) post–earnings announcement drift signal is the ninth most heavily cited RPS.

[7] Jegadeesh and Titman (1993) examine 32 RPS by varying both the number of months in their lagged-return RPS and the number of months in the post-signal holding period. We focus on their 6-month lagged-return RPS as representative of the 32 they study because the returns produced by that signal are not the largest and are not sensitive to the number of months in the holding period (p. 69). We only include the 6-month lagged-return RPS in our supraview database, not all 32 RPS.

[8] We do not seek to identify working papers before the advent of SSRN. For published papers for which we do not have an electronic copy of the working paper, we set the date of the first working paper to be two years prior to the paper's publication date.

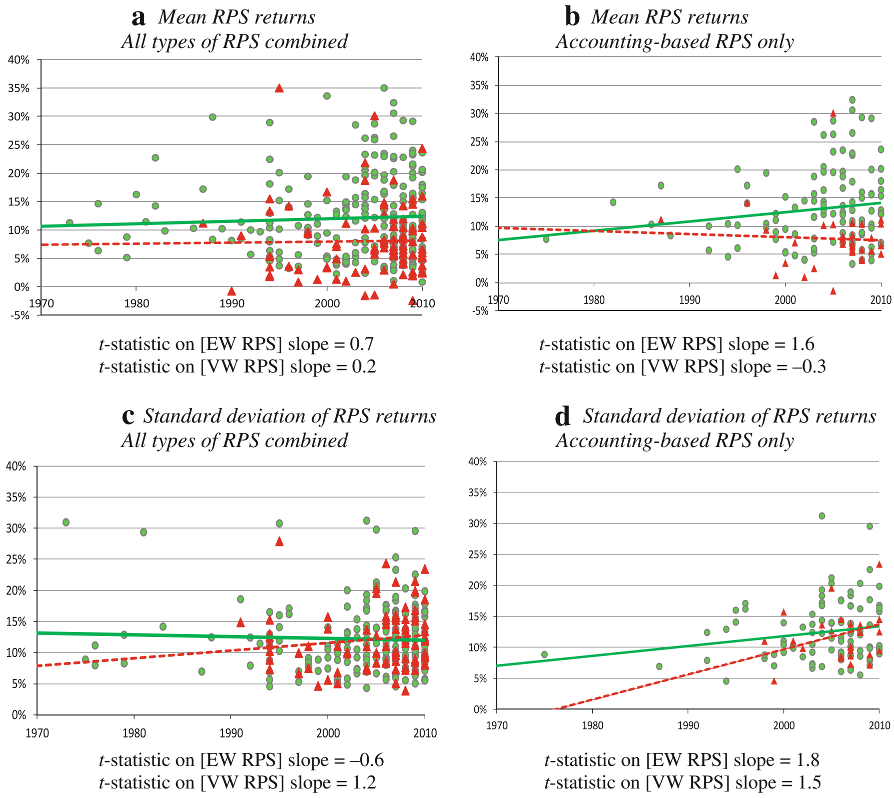


Fig. 2 Mean annualized returns and annualized standard deviation of returns earned by return predictive signals (RPS) plotted according to the year in which the RPS was first publicly reported, 1970–2010. *Green* (*red*) denotes equally weighted [EW] (value-weighted [VW]) RPS returns. *T*-statistics pertain to the estimated slope coefficient in a regression of mean annualized RPS returns on the year in which the RPS was first reported (Color figure online)

weighted and value-weighted RPS returns over the full 40-year period from 1970 through 2011.

We interpret the stability of the return properties of newly discovered RPS as consistent with the proposition that the process of RPS discovery is academic in the positive sense of the word—namely, that it happens independent of the investment potential of the discovered RPS and that private property rights to economic rents from newly discovered RPS are abandoned by their discoverers through the process of academic publication. Were this not the case and academics pursued the discovery and publication of new RPS either explicitly or implicitly based on their real-world investment potential, it seems reasonable to expect that the first RPS to have been discovered would on average have been those with higher mean returns, lower variability, and higher Sharpe ratios, resulting in a negative correlation between such investment performance characteristics of newly discovered RPS and calendar time.

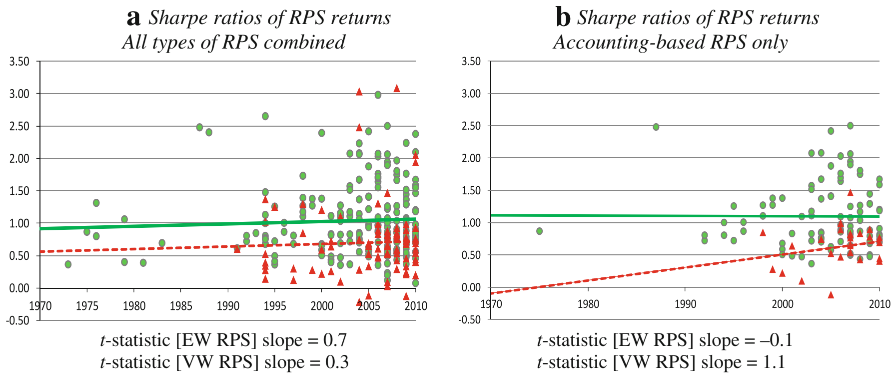


Fig. 3 Annualized Sharpe ratios of the returns earned by return predictive signals (RPS) plotted according to the year in which the RPS was first reported, 1970–2010. *Green* (*red*) denotes the Sharpe ratios of equally weighted [EW] (value-weighted [VW]) RPS returns. *T*-statistics pertain to the estimated slope coefficient in a regression of annualized Sharpe ratios of RPS returns on the year in which the RPS was first reported (Color figure online)

3.5.6 Riskiness of RPS considered individually versus in portfolio

Next we examine the relation between RPS returns and risk. One of the most common risk/return measures in the finance literature and on Wall Street is the Sharpe ratio, measured as the ratio of the excess return of an investment (portfolio returns minus risk-free rate, or hedge return) to its return volatility or standard deviation. For example, Bailey and López de Prado (2012) state that "[t]he Sharpe ratio … has become the gold-standard to evaluate portfolio managers in the hedge fund industry. Most hedge funds require any candidate manager or strategy to pass a set of fixed thresholds with regards to Sharpe ratios and track record length in order to be allocated capital."[9] According to static mean–variance portfolio theory, an investor with negative exponential utility maximizes the Sharpe ratio in determining his or her asset allocation.

The seventh new result we uncover by taking the supraview of RPS is that while RPS with higher mean returns are riskier in the sense that they have larger standard deviations of returns, they also have higher Sharpe ratios. In regressions of mean RPS returns on their associated standard deviations of returns or Sharpe ratios shown in Fig. 4, all slope coefficient estimates are significantly positive.

We argue that while the presence of a positive correlation between mean returns and the standard deviation of returns is intuitively appealing, the presence of a positive correlation between mean returns and Sharpe ratios is somewhat surprising. This is because if market prices are set by sophisticated investors, we expect the correlation between returns and Sharpe ratios to be zero or even negative. If the risk of an RPS is fully captured by the standard deviation of its returns over time, then in a rational market where an increase in expected return would be accompanied by an

[9] As of the year 2012, Mr. López de Prado was Head of Global Quantitative Research at Tudor Investment Corp., which in August 2011 had a reported $11 billion of assets under management.

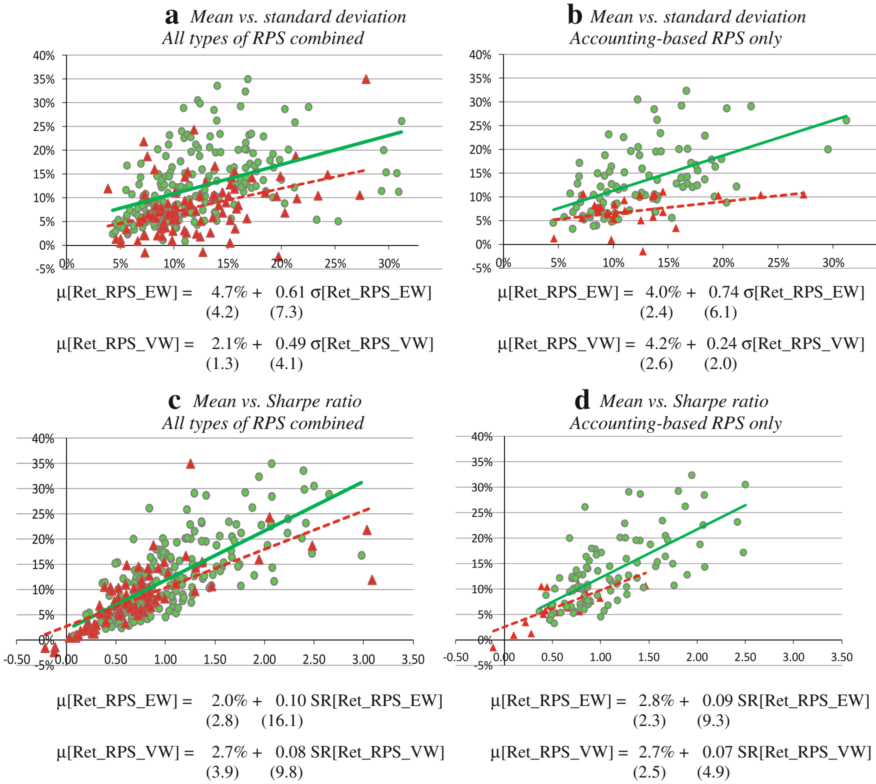


Fig. 4 Mean annualized returns earned by return predictive signals (RPS) plotted on vertical axes according to the annualized standard deviations (horizontal axes, **a**, **b**) and the annualized Sharpe ratios (horizontal axes, **c**, **d**) of those returns for RPS first reported during 1970–2010. *Green* (*red*) denotes equally weighted (value-weighted) RPS returns (Color figure online)

appropriately higher degree of risk, Sharpe ratios should at best be equal for all RPS, and perhaps more likely negatively related to return to the extent that implementing a low return but high Sharpe ratio RPS requires leverage to achieve medium-to-high absolute levels of return. A positive correlation between the mean returns and Sharpe ratios of RPS suggests either that the market is inefficient or that the standard deviation of returns is an incomplete proxy for the risk of an RPS.

3.5.7 Return properties of academic versus practitioner RPS

A further result we document about RPS as a whole is that the RPS that large, sophisticated investors publicly report using are a truncated subset of all academically discovered and publicly disclosed RPS. We visually display this truncation in Fig. 5. In panel A we repeat panel c of Fig. 4 that plots the mean returns of academically discovered and reported RPS against their associated Sharpe ratios, while in panel B we show the mean returns of RPS that J.P. Morgan disclosed that it made available to its clients for the construction of their investment portfolios

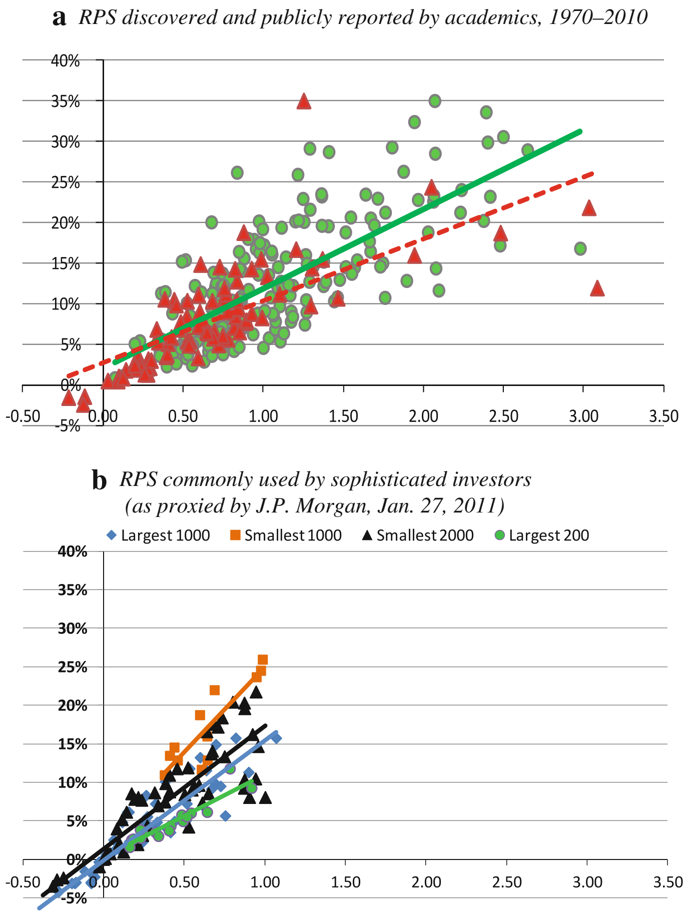


Fig. 5 The annualized mean returns earned by academic and nonacademic return predictive signals (RPS) plotted against their annualized Sharpe ratios. RPS discovered by academics between 1970 and 2010 are shown in (**a**), while the RPS reported by and defined in J. P. Morgan's *US Factor Reference Book* dated Jan. 27, 2011 are shown in (**b**). The returns and Sharpe ratios in (**a**) are taken from the underlying academic papers and do not necessarily represent the performance of the signal during 1995–2010, while those in (**b**) are always for the Russell 3000 during 1995–2010. In (**a**) *green* (*red*) denotes mean returns and Sharpe ratios based on equally weighted (value-weighted) RPS (Color figure online)

(*US Factor Reference Book,* Jan. 27, 2011). While J. P. Morgan is clearly but one of a large number of sophisticated investors in the equity markets, we conjecture that there is no a priori reason to suppose that they are a biased proxy for the population of sophisticated equity investors.

A visual comparison of panels a and b of Fig. 5 highlights that the RPS reported by J. P. Morgan have a maximum Sharpe ratio of about 1.1, regardless of whether implementation of the RPS is restricted to large-cap or small-cap firms. In contrast, the maximum Sharpe ratio for academically discovered and reported RPS is 3.1, and of all equally weighted (value-weighted) academic RPS, 36 % (14 %) exceed 1.1.

We interpret these results as indicating either that sophisticated investors such as J. P. Morgan are unaware of academically discovered RPS that have Sharpe ratios above 1.1, or that they are aware of these RPS but choose not to publicly disclose that they make them available to their clients. Moreover, we cannot determine whether a sophisticated investor such as J. P. Morgan in fact does tell its clients about academically discovered and reported RPS with Sharpe ratios above 1.1. One reason that an entity such J. P. Morgan might not inform its clients about such RPS could be that it only uses the RPS for investing its own capital, not that of its clients.

4 Practitioner and academic implications of the RPS supraview

4.1 Potential for improved practitioner investment performance through multiple RPS

One question that surfaces in light of the more than 330 RPS that have been discovered and reported by business academics in the past 40 years is the degree to which the population of RPS can be used to improve the performance of a sophisticated investor's US equity portfolio. We look to provide guidance on this issue in two ways. First, we theoretically and empirically describe the Sharpe ratios that are expected to be achieved when multiple RPS are combined into an RPS portfolio. Second, we outline the Sharpe ratios that can be expected to obtain when a portfolio of RPS is combined with the overall US stock market.

We estimate the degree to which a portfolio of RPS achieves superior performance over any single RPS via the algebraic machinery described in Bailey and López de Prado (2012). Bailey and López de Prado calculate that if the returns of S return predictive signals are described by

$$r_s \sim N\left(\mu_s, \sigma_s^2\right), \quad for\, s = 1, \ldots, S, \tag{1}$$

and if an equal-volatility portfolio weighting of the RPS is constructed per

$$\omega_s = \frac{1}{S\sigma_s}, \tag{2}$$

then the Sharpe ratio of the equal-volatility-weighted RPS portfolio P is given by

$$SR_P = \overline{SR}\sqrt{\frac{S}{1 + (S-1)\overline{\rho}}}, \tag{3}$$

where $\overline{SR} = \frac{1}{S}\sum_{s=1}^{S} \frac{\mu_s}{\sigma_s}$ is the average Sharpe ratio of the individual RPS and $\overline{\rho} = \frac{2\sum_{s=1}^{S}\sum_{s=s+1}^{S}\rho_{s,t}}{S(S-1)}$ is the mean signed cross-correlation of RPS returns.

Two attractions of the equal-volatility-weighting scheme used by Bailey and López de Prado over alternative ways of combining multiple RPS into a portfolio (such as mean–variance optimization) are that their approach can combine 300 RPS as easily as 3 RPS and that it allows for the Sharpe ratio SR_p of a set of RPS to be succinctly described by three parameters: the number of RPS, the average Sharpe ratio of the RPS, and the average cross-correlation between the RPS returns.[10] Within this framework, Eq. (3) also reveals that, all else held equal, SR_p is a linear function of $\overline{SR}$, a convex function of S, and a concave function of $\overline{\rho}$.[11]

We apply Eq. (3) to our RPS database in three steps. First, we arrive at the theoretical relations between SR_p and $\{S, \overline{SR}$ and $\overline{\rho}\}$ by fixing $\overline{SR}$ at the empirical value reported in the underlying RPS papers and then analytically varying S and $\overline{\rho}$. Second, again fixing $\overline{SR}$ at its empirical value reported in the underlying RPS papers, we estimate $\overline{\rho}$ using a sample of signals from our RPS database and apply that estimate back into Eq. (3) to determine SR_p as a function of S. Third, we estimate both $\overline{\rho}$ and $\overline{SR}$ from the sample of signals and apply these estimates back into Eq. (3).

The results of the first step are shown in Fig. 6 for equally weighted RPS. Panel A reports SR_p as a function of S for varying levels of $\overline{\rho}$, given that the mean Sharpe ratio of the $n = 208$ RPS for which a Sharpe ratio is reported or is calculable is 1.04 (see Table 4, panel A). Panel B reports $\overline{SR}$ as a function of $\overline{\rho}$ for varying levels of S, given the same mean Sharpe ratio of 1.04. Panel A shows that while the maximum Sharpe ratio that can be obtained from a set of RPS increases in S, it increases far more for decreases in $\overline{\rho}$. For example, when $\overline{SR} = 1.04$, the Sharpe ratios achieved when $S = 5$ are 1.08 when $\overline{\rho} = 0.9$, 1.19 when $\overline{\rho} = 0.7$, 1.34 when $\overline{\rho} = 0.5$, 1.57 when $\overline{\rho} = 0.3$, 1.97 when $\overline{\rho} = 0.1$, and 2.12 when $\overline{\rho} = 0.05$. If instead $S = 330$ (more than a 60-fold increase in S), the Sharpe ratios obtained are 1.10 when $\overline{\rho} = 0.9$, 1.24 when $\overline{\rho} = 0.7$, 1.47 when $\overline{\rho} = 0.5$, 1.89 when $\overline{\rho} = 0.3$, 3.24 when $\overline{\rho} = 0.1$, and 4.52 when $\overline{\rho} = 0.05$. Panel B makes the same point in a slightly different way by analytically showing that Sharpe ratios increase as S increases, but at a decreasing rate, while Sharpe ratios increase as $\overline{\rho}$ decreases, but at an increasing rate.

Concerning the second and third steps, due to the colossal time and expense that would be required to measure $\overline{\rho}$ by calculating all of the more than 55,000 return cross-correlations for the population of more than 330 RPS, we instead seek to empirically translate the theoretical results reported in Fig. 6 by sampling 39 signals that we judge to be readily programmable through CRSP, Compustat, and I/B/E/S and for which reasonably complete data are available during the period January 1985–December 2011 (see Table 6). Of the sampled RPS, 26 are accounting-based, 10 are finance-based, and 3 are other-based.

Because not all the sampled RPS use signals that are available with the same frequency and not all of the sampled RPS were originally used to predict returns over the same horizon, we align signals and returns in calendar time and compute monthly RPS returns. Imposing a calendar-time approach echoes the finding that 56 % of RPS papers use monthly returns in their analysis (Table 3, panel C). Each

[10] An alternative method of combining individual RPS into a portfolio that can accommodate a large number of RPS is the parametric portfolio policies (PPP) approach of Brandt et al. (2009). In the context of a relatively small number of RPS, the PPP approach has been studied by Green and Hand (2011).

[11] Bailey and López de Prado (2012) employ a "naïve" equal-volatility-weighted portfolio approach because such an approach greatly simplifies the algebra without sacrificing much in the way of portfolio optimization. The equal-volatility approach was first used by DeMiguel et al. (2009), who compare 14 models of optimal asset allocation and find that no single model consistently delivers a Sharpe ratio or certainty equivalent return that is higher than the equal-volatility-weighted approach.

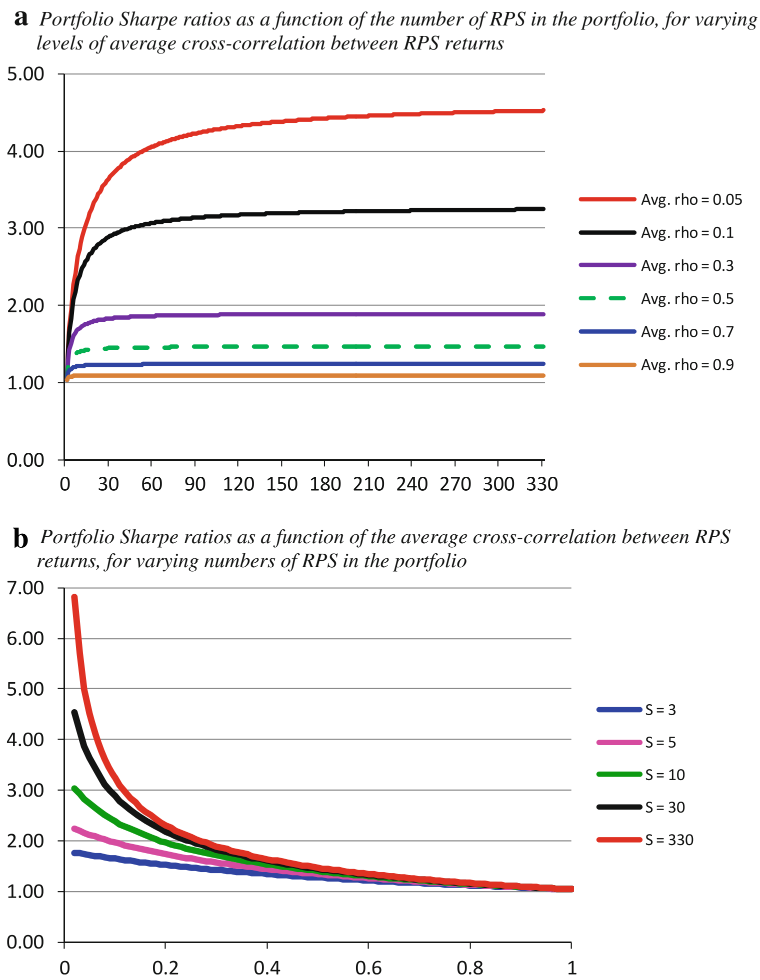


Fig. 6 Portfolio Sharpe ratios as an analytical function of the number of RPS and the average cross-correlation of equally weighted RPS returns, given a mean RPS Sharpe ratio of 1.04

RPS is created based on the most recently available information as of the end of each month. Accordingly, at the end of each month we rank stocks by RPS into deciles and create a dollar-neutral hedge portfolio that goes long in stocks in the decile that is expected to generate high returns and goes short in stocks in the decile that is expected to generate low returns. We then hold these positions for 1 month and repeat the procedure. We use these hedge returns to estimate and study the correlation structure of the RPS population.[12]

[12] An alternative approach would be to estimate the correlation structure of the underlying signals rather than the correlation structure of the RPS returns. We choose to estimate the correlation structure of the returns to be consistent with the focus on investors' portfolio returns within the equal-volatility-weighted portfolio framework.

Table 6 Key descriptors of the set of 39 readily programmed RPS from our RPS population database

No.	Author(s)	Signal	Equally weighted returns			Value-weighted returns		
			Mean return (%)	SD (%)	Sharpe ratio	Mean return (%)	SD (%)	Sharpe ratio
	–	Risk-free rate (1-month treasury bill)	4.0	0.7		4.0	0.7	
	–	Market less risk-free rate	8.8	19.1	0.46	7.1	16.1	0.44
1	Banz (1981)	Firm size	13.8	20.1	0.69	0.4	19.6	0.02
2	Rosenberg et al. (1985)	Book-to-market	14.6	13.9	1.05	5.6	17.9	0.32
3	Jegadeesh (1990)	12-month momentum	−3.6	33.4	−0.11	18.0	34.2	0.53
4	Jegadeesh and Titman (1993)	One-month momentum	27.5	26.6	1.03	2.5	25.5	0.10
5	Gettleman and Marks (2006)	Change in 6-month momentum	9.6	17.9	0.54	6.5	21.3	0.31
6	Cooper et al. (2008)	Asset growth	22.2	14.7	1.51	8.9	15.5	0.57
7	Basu (1977)	Earnings-to-price	−4.7	22.9	−0.20	2.4	22.9	0.11
8	Sloan (1996)	Working capital accruals	6.8	7.2	0.94	4.7	11.7	0.40
9	Hafzalla et al. (2007)	Percentage accruals	2.7	14.3	0.19	−1.4	15.3	−0.09
10	Chemmanur and Yan (2009)	Change in advertising expense	−0.4	14.4	−0.03	8.8	14.2	0.62
11	Chen and Zhang (2010)	Capital expenditures and inventory	18.2	11.7	1.55	6.6	11.7	0.57
12	Pontiff and Woodgate (2008)	Change in shares outstanding	12.6	12.1	1.03	7.0	11.1	0.63
13	Richardson et al. (2005)	Change in long-term debt	12.3	8.4	1.46	5.2	11.8	0.44
14	Richardson et al. (2005)	Change in common shareholder equity	11.5	12.0	0.96	5.8	11.8	0.49
15	Soliman (2008)	Industry-adjusted change in profit margin	0.2	8.6	0.03	2.9	11.7	0.25
16	Soliman (2008)	Industry-adjusted change in asset turnover	4.6	5.5	0.84	4.4	9.6	0.45
17	Thomas and Zhang (2011)	Change in tax expense	13.3	8.0	1.66	6.5	12.5	0.52
18	Rendleman et al. (1982)	Unexpected quarterly earnings	20.4	8.9	2.28	11.8	15.4	0.77
19	Brandt et al. (2008)	Three-day return around earnings announcement	12.8	8.6	1.49	6.7	11.6	0.58
20	Chandrashekar and Rao (2009)	Cash-to-price	7.8	10.5	0.74	4.3	11.1	0.38

Table 6 continued

No.	Author(s)	Signal	Equally weighted returns			Value-weighted returns		
			Mean return (%)	SD (%)	Sharpe ratio	Mean return (%)	SD (%)	Sharpe ratio
21	Hou and Robinson (2006)	Industry sales concentration	4.0	12.3	0.33	−0.3	12.8	−0.03
22	Balakrishnan et al. (2010)	ROA	11.1	23.4	0.47	8.5	22.5	0.38
23	Novy-Marx (2012)	Gross profitability	0.4	13.5	0.03	5.9	14.9	0.39
24	Lerman et al. (2008)	Abnormal volume in earnings announcement month	6.6	7.1	0.93	3.8	12.4	0.30
25	Chordia et al. (2001)	Dollar trading volume from month $t-2$	13.3	18.2	0.73	−0.2	12.1	−0.01
26	Bali et al. (2011)	Maximum daily return in prior month	0.4	29.4	0.02	10.0	30.5	0.33
27	Frazzini and Lamont (2006)	Earnings announcement month	4.8	5.9	0.81	6.6	6.5	1.03
28	Diether et al. (2002)	Dispersion in forecasted EPS	12.4	15.7	0.79	8.5	19.8	0.43
29	Hawkins et al. (1984)	Change in forecasted EPS	12.9	9.6	1.35	5.1	12.9	0.40
30	Bauman and Dowen (1988)	Forecasted growth in 5-year EPS	3.6	27.9	0.13	0.4	29.9	0.01
31	Bandyopadhyay et al. (2010)	Accrual volatility	4.3	22.3	0.19	5.4	18.3	0.29
32	Browne and Rowe (2007)	Return on invested capital	−0.1	22.1	0.00	10.8	23.5	0.46
33	Eberhart et al. (2004)	R&D increase	4.5	18.3	0.25	0.2	11.9	0.01
34	Huang (2009)	Cash flow volatility	3.0	22.2	0.14	8.5	18.6	0.46
35	Thomas and Zhang (2002)	Changes in inventory	13.7	8.2	1.67	6.0	12.1	0.49
36	Ang et al. (2006)	Return volatility	−3.6	33.1	−0.11	17.3	36.0	0.48
37	Asness et al. (2000)	Industry-adjusted change in employees	12.0	8.6	1.39	5.9	11.2	0.53
38	Bazdresch et al. (2010)	Employee growth rate	16.1	12.3	1.31	4.9	13.3	0.37
39	Datar et al. (1998)	Turnover	30.0	27.8	1.08	4.0	24.1	0.17
		Mean across $N = 39$ RPS	9.0	15.8	0.75	5.9	16.9	0.37

Each RPS is implemented in such a way that it generates a positive expected mean long/short hedge return. Mean returns and the standard deviation of monthly returns are annualized by multiplying monthly returns by 12 and the standard deviation of monthly returns by sqrt(12)

For each RPS and for both equally weighted and value-weighted returns, we compute and report in Table 6 the mean annualized return, the annualized standard deviation of returns, and the annualized Sharpe ratio. Although each RPS is constructed to reflect the intent of the strategy as originally proposed in the underlying paper in which the RPS was first reported, of the 39 signals, 5 (3) equally weighted (value-weighted) mean returns are not positive using our monthly implementation approach and time period.[13] We attribute this to two aspects of our methodology. First, our approach is uniform and standardized, and as such it may miss key nuances pertaining to the signal and/or data inclusion criteria that were important aspects of the original RPS papers. Second, we calculate returns both before and after the discovery and public reporting of the RPS. Given recent evidence reported at both the single RPS and global RPS levels that RPS returns decay to some degree after they are publicly disclosed (Green et al. 2011; McLean and Pontiff, 2012),[14] this likely dilutes and adds noise to the mean RPS returns we report in Table 6.[15]

Descriptive statistics on the average signed cross-correlations among the monthly returns of our sample of 39 RPS over the period January 1985–December 2011, together with the average signed correlations between RPS returns and the returns on the US equity market, are reported in panels A and B of Table 7, respectively.[16] We compute and report the average signed correlations between RPS returns and the returns on the US equity market in order to begin to gauge the extent to which an investor might benefit from tilting a diversified equity portfolio toward a portfolio of RPS.

The average signed cross-correlation of monthly returns in our sample of 39 RPS is small, measuring just 0.05 for equally weighted and value-weighted RPS returns alike (Table 7, panel A).[17] Per Bailey and López de Prado (2012) and Eq. (3), such a small average cross-correlation implies that when multiple RPS are combined on an equal-volatility-weighted basis, a portfolio of 3 (30, 300) RPS has an expected

[13] We also note that the difference between the mean excess equally weighted and value-weighted annual market returns reported in Table 6 is just 1.7%, as compared to 2.9% in the RPS population (cf. the means reported in Table 5, panel E versus those in Table 4, panel E). This simply reflects the fact that the difference between the mean excess equally weighted and value-weighted annual market returns in the period 1985–2011 is 1.2%, as compared to 4.5% in the period 1970–1984.

[14] In a paper contemporaneous to our present study, McLean and Pontiff (2012) find using a sample of 82 firm-specific characteristics that the average post-publication decay in the return to an RPS, which they attribute to both statistical bias and price pressure from aware investors, is about 35% and statistically different from both 0% and 100%. Consistent with informed trading, they document that after an RPS is published it experiences higher volume, variance, and short interest, as well as higher correlations with other RPS that have already been published. Consistent with costly (limited) arbitrage, McLean and Pontiff show that the post-publication decline is greater for RPS whose stocks are large, are liquid, have high dividend yields, and have low idiosyncratic risk.

[15] In unreported tests we divided the window January 1985–December 2011 into five-year periods and, consistent with the presence of some alpha decay, find some (albeit weak) evidence that the dispersion of Sharpe ratios and of annualized returns for equal-weighted hedge portfolio returns declined until 2010.

[16] The individual cross-correlations are available from the authors upon request. We do not provide correlation tables because it is all but impossible to fit 741 cross-correlations onto a single page without the font size becoming illegible.

[17] Untabulated results show that the five-year average signed cross-correlations among RPS returns have ranged between approximately 0.01 and 0.08 without any clear linear time-trends.

Table 7 Average signed and average absolute cross-correlations among the monthly returns of 39 readily programmed RPS from our database of RPS discovered and publicly reported during 1970–2010, and between RPS returns and the returns on the US equity market. Monthly RPS returns are calculated by implementing each RPS over the period 1985–2011 (both before and after the RPS was discovered and publicly reported), such that it generates a positive expected mean long/short hedge return

Panel A: *Correlations among RPS returns*

	Equally weighted RPS returns	Value- weighted RPS returns
Average signed cross-correlation among RPS returns	0.05	0.05
Average absolute cross-correlation among RPS returns	0.29	0.22
Percentage of cross-correlations < 0	47 %	44 %
Percentage of cross-correlations > 0	53 %	56 %
Average cross-correlation for negative correlations	–0.25	–0.19
Average cross-correlation for positive correlations	0.33	0.24

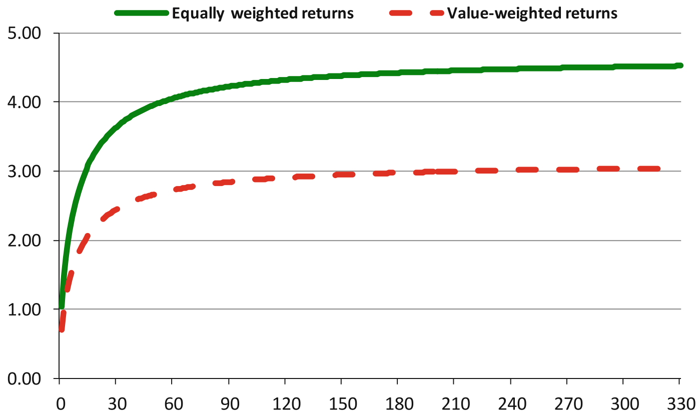
Panel B: *Correlations between RPS returns and US equity market returns*

	Equally weighted RPS and US equity market returns	Value- weighted RPS and US equity market returns
Average signed correlation between RPS returns and return on US equity market	–0.16	–0.17
Average absolute correlation between RPS returns and return on US equity market	0.36	0.27
Percentage of correlations < 0	67 %	79 %
Percentage of correlations > 0	33 %	21 %
Average correlation among negative correlations	–0.39	–0.27
Average correlation among positive correlations	0.30	0.25

annualized Sharpe ratio that is 1.65 (3.50, 4.33) times the mean Sharpe ratio of its component RPS. While this is impressive, we highlight the fact that the magnitude of the RPS portfolio's Sharpe ratio depends on the mean Sharpe ratio of the signals in the portfolio. We therefore take two approaches to estimating this critical variable, based on which we then trace out the resulting expected Sharpe ratios of portfolios of varying numbers of RPS.

Our first approach is to take the mean Sharpe ratio of a randomly chosen portfolio of RPS to be the mean Sharpe ratio of all signals in the RPS database, as reported in the original papers. This is $\overline{SR} = 1.04$ for equally weighted returns (Table 4, panel A) and $\overline{SR} = 0.70$ for value-weighted returns (Table 5, panel A). Our second approach is to take the mean Sharpe ratio of the sample of $n = 39$ readily programmed RPS, which is $\overline{SR} = 0.75$ for equally weighted returns and $\overline{SR} = 0.37$ for value-weighted returns (Table 6). Ignoring any implementation costs, we view the first approach as providing upper-bound or "best case" RPS portfolio Sharpe ratios and the second approach as providing lower-bound or "worst case" RPS portfolio Sharpe ratios. This is because we use the same data to calculate the mean Sharpe ratios reported in Table 6 and the mean cross-correlations reported in Table 7. Such a readily implementable but less-

a *Portfolio Sharpe ratios as a function of the number of RPS in the portfolio, where the mean Sharpe ratios of the individual equally weighted (value-weighted) RPS are taken per panel A of Table 4 (panel A of Table 5) to be 1.04 (0.70), the population means*



b *Portfolio Sharpe ratios as a function of the number of RPS in the portfolio, where the mean Sharpe ratios of the individual equally weighted (value-weighted) RPS are taken per Table 6 to be 0.75 (0.37), the means of the 39 RPS sampled from the population*

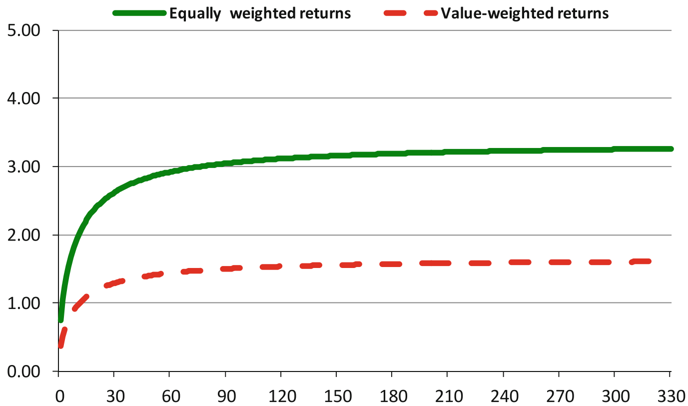


Fig. 7 Theoretically expected Sharpe ratios of portfolios of RPS as a function of (1) the number of RPS in the portfolio, and (2) the mean Sharpe ratio of the individual RPS in the portfolio. In both panels, the average signed cross-correlation among equally weighted and value-weighted RPS returns is taken to be its empirical value of 0.05 (Table 7, panel A)

than-sophisticated approach necessarily includes in the calculation of RPS Sharpe ratios returns from both before and after the RPS were publicly first disclosed. Since trading on RPS makes average RPS returns decline after they are first publicly reported (Green et al. 2011; McLean and Pontiff, 2012), this means that the Sharpe ratios reported in Table 6 are diluted compared to the Sharpe ratios reported in the underlying original RPS papers.

In panels a and b of Fig. 7 we report the results of applying the two approaches outlined above. Both panels indicate that there may be large investment performance gains to be had for practitioners who can invest in multiple RPS, especially at very low costs of implementation. For example, the performance curves in panel A indicate that the best-case expected Sharpe ratio of the equally weighted returns from a portfolio of 3 (30, 300) randomly chosen RPS is 1.72 (3.64, 4.51), while the best-case expected Sharpe ratio of the value-weighted returns from a portfolio of 3 (30, 300) randomly chosen RPS is 1.16 (2.45, 3.04). The Sharpe ratios in panel B are not as spectacular as those in panel A but are nevertheless impressive: the worst-case expected Sharpe ratio of the equally weighted returns from a portfolio of 3 (30, 300) randomly chosen RPS is 1.24 (2.46, 3.25), while the worst-case expected Sharpe ratio of the value-weighted returns from a portfolio of 3 (30, 300) randomly chosen RPS is 0.61 (1.29, 1.60).

Because our use of Bailey and López de Prado's approach to constructing portfolios is new to the accounting literature, we seek to additionally validate their analytics by means of an empirical simulation. Specifically, using the sample of 39 RPS and their empirical mean returns, standard deviation of returns, and Sharpe ratios, we adopt the following multi-step procedure, where without loss of generality the steps are applied to equally weighted RPS returns. First, we randomly sample one RPS and identify its empirical Sharpe ratio per Table 6. We do this 500 times, then calculate the mean of the 500 empirical Sharpe ratios. Second, we randomly sample two RPS, combine them using equal-volatility weights into a portfolio, and based on their empirical cross-correlation calculate that portfolio's Sharpe ratio. We do this 500 times, then calculate the mean of the 500 portfolios' Sharpe ratios. Third, we repeat the second step using three randomly sampled RPS, and so on all the way up to sampling 30 randomly selected RPS. Fourth, we trace out the series of mean Sharpe ratios and compare the result to the series of theoretically expected Sharpe ratios plotted in panel b of Fig. 7. We do the same for value-weighted returns. The results are shown in Fig. 8, where it

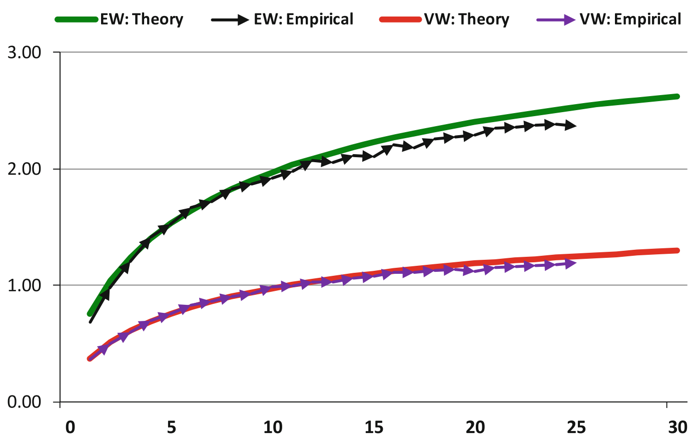


Fig. 8 Comparison of the expected theoretical Sharpe ratios versus the empirical mean Sharpe ratios of portfolios of randomly selected RPS as a function of (1) the number of RPS in the portfolio and (2) the mean Sharpe ratio of the individual RPS in the portfolio. In both panels, the average signed cross-correlation among equally weighted and value-weighted RPS returns is taken to be its empirical value of 0.05 (Table 7, panel A)

can be seen that the empirical average Sharpe ratios closely match the theoretical expected Sharpe ratios.

We conclude our investigation into the improvements that multiple RPS may offer to investment practitioners by noting that investors may choose to allocate funds to both RPS and other asset classes. We therefore shed preliminary light on the performance of a portfolio of RPS and the US equity market by reporting in panel B of Table 7 that mean correlation between the equally weighted and value-weighted monthly returns on individual RPS and the monthly excess returns on the equally weighted and value-weighted US stock market per CRSP are surprising in that they are negative, measuring −0.16 and −0.17, respectively. The negative correlation implies that the Sharpe ratios obtained from combining portfolios of RPS with the overall US equity market can be expected to materially exceed that of both the portfolio of RPS and the US equity market considered separately.[18]

4.2 Academic confidence in the determination of new RPS

It might be tempting to infer from the approximately zero average signed cross-correlations reported in panel A of Table 7 that an academic who discovers what he or she proposes is a brand new RPS does not need to orthogonalize the returns of the candidate RPS against the returns of existing RPS. However, this would be incorrect, because a zero average signed RPS cross-correlation could hide the offsetting presence of signals whose returns are highly negatively and highly positively cross-correlated. Such a possibility can only be ruled out if the average absolute cross-correlation among the RPS is also zero.

We therefore measure and report the average absolute cross-correlations among the 39 sampled RPS in panel A of Table 7. We find that the average absolute cross-correlations are materially greater than zero, measuring 0.29 for equally weighted returns and 0.22 for value-weighted returns.[19] The percentage of negative cross-correlations is 47 % (44 %) for equally weighted (value-weighted) returns, and the average negative cross-correlation is smaller in absolute magnitude than is the average positive cross-correlation. Taken as a whole, the statistics reported in panel A of Table 7 informally reject two propositions: that all cross-correlations among RPS returns are zero and that all cross-correlations among RPS returns are very positive or very negative.

To therefore empirically assess the degree to which the magnitude of RPS cross-correlation affects the validity of inferences made by a researcher who discovers what he or she hypothesizes is a truly new RPS, we adopt the following procedure. First, from our subset of 39 RPS chosen from the population of 330 RPS, we randomly select one RPS. Second, we randomly select one other RPS from the 39 RPS and regress the returns of the first randomly selected RPS on the returns of the

[18] For example, if the correlation between a portfolio of RPS and the equity market is −0.16, then an equal-volatility weighted portfolio of RPS and the equity market will have an expected Sharpe ratio that is more than 20% larger than that of the component portfolio of RPS and 100% larger than that of the overall US equity market.

[19] In untabulated analysis, we find that five-year average absolute cross-correlations range between 0.23 and 0.38, and that they tend to be larger for equally weighted returns than for value-weighted returns.

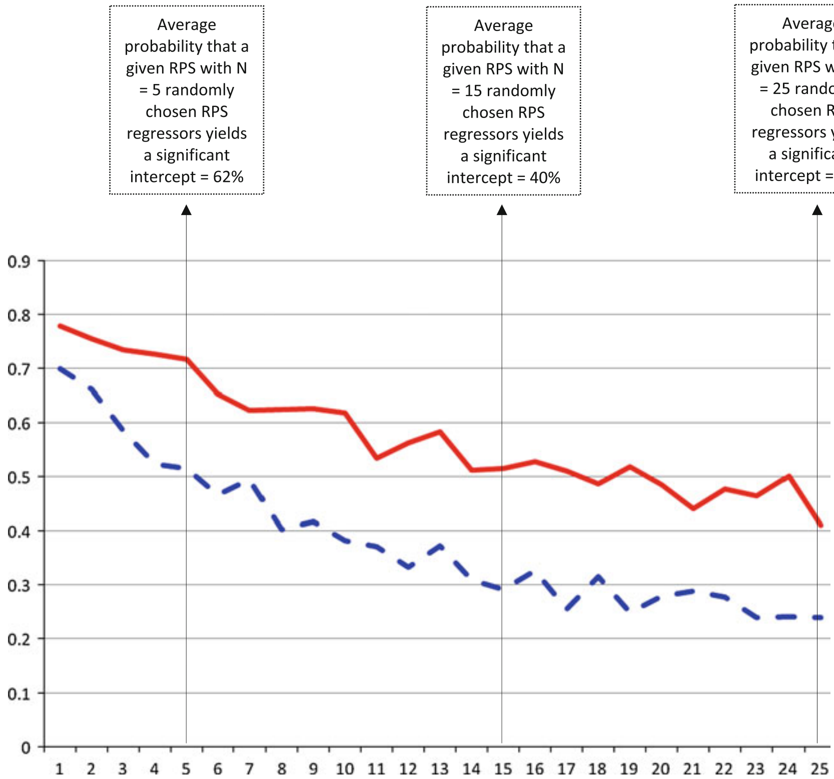


Fig. 9 Empirical estimates of the probability of observing statistically significant alpha on a given randomly chosen RPS when the hedge returns of that RPS are orthogonalized against the hedge returns of up to 25 other randomly chosen RPS. The group of RPS used in this analysis is the subset of the 39 readily programmed RPS described in Table 6. Results using equally weighted (value-weighted) RPS returns are shown in the *solid red* (*dashed blue*) *line* (Color figure online)

other randomly selected RPS, noting whether the estimated intercept is statistically significant at the 5 % level. Third, we repeat the first and second steps 500 times and measure the percentage of the 500 repetitions that result in a significant intercept. Fourth, we repeat steps one through three, but in step two we randomly select two other RPS in the 39 RPS; on completion of that substep, we repeat by randomly selecting three other RPS; and so on. Seen to completion, this procedure yields the percentage of times that a randomly selected RPS and N randomly selected other RPS result in a statistically significant intercept.

We graphically report the resulting percentages in Fig. 9, where the x-axis is the number of N randomly selected other RPS used to explain the returns to a given randomly selected RPS, and the y-axis is the probability that a randomly selected RPS and N randomly selected other RPS result in a statistically significant intercept. Figure 9 indicates that selecting a single additional explanatory factor yields a 74 % probability that a selected signal is judged significant. This probability falls to 62 % when $N = 5$, to 50 % when $N = 10$, to 40 % when $N = 15$, and to 32 % when $N = 25$. That is, even after controlling for 25 other RPS, there is a one-in-three chance that the returns from a newly discovered RPS (whose raw returns are very likely to be significantly positive—otherwise the RPS is not likely to be pursued further by the discovering academic) will remain statistically significantly positive.

We interpret the evidence summarized in Fig. 9 as being informative to academics who uncover what they think are new RPS, in that Fig. 9 indicates that researchers may not need to orthogonalize the returns of the new RPS against the returns from every single pre-existing RPS. We note, however, that while our approach of randomly selecting factors from the RPS to be included as controls in the regressions is objective and scientifically replicable, it may not be representative of what a researcher would actually do based on prior research he or she is aware of, or on the underlying research question, or on the similarity between the newly discovered RPS and previously discovered RPS.[20] We seek to address this concern in the following way. Rather than selecting random RPS as factors, for each RPS hedge portfolio return we select up to 10 of those RPS from the other RPS that generate the highest adjusted R-square value in the orthogonalizing regression. We find that such regressions generate 21 (12) reliably negative intercepts using the equally weighted (value-weighted) returns. This result echoes what we report in Fig. 9, in the sense that even selecting those 10 factors that best explain the returns to RPS, 46 % (69 %) of the equally weighted (value-weighted) RPS maintain a reliably positive alpha.

5 Conclusions

In this paper, we have sought to inform both investment academics and practitioners by taking a "forest-level" or supraview of the signals that accounting and finance academics have discovered and made public over the past 40 years and that predict (usually the cross-section of) returns in US stock markets. Rather than seeking to discover a single new RPS, our approach has been to describe and analyze an approximation of the population of RPS that have already been discovered. In doing so, we have sought to take an initial step of response to the call made by Richardson et al. (2010) that researchers in the RPS area begin to move away from what they describe as "the haphazard nature of this line of research [into RPS]" and instead move toward imposing more structure on the extant anomalies literature. The structure that our paper contributes to the literature is a robust description of the population of RPS across a number of financial and nonfinancial dimensions.

Through our supraview, we have uncovered several new facts about RPS. These include the observations that many more RPS have been identified than is typically assumed; that the statistical properties of newly discovered RPS have remained stable over time; that the returns and Sharpe ratios earned by heavily cited RPS such as accruals and momentum are lower than those of the median RPS; and that while RPS with higher mean returns are riskier in the sense that they have larger time-series standard deviations of returns, they also have higher Sharpe ratios.

[20] Alternatively, a researcher may choose simply to include all available factors—a prospect we would consider a daunting task.

Seeking to contribute to practice, we have presented evidence that suggests that the investment performance available to practitioners from exploiting the population of RPS may be large, primarily because we estimate that the average signed cross-correlation among RPS returns is close to zero, but also because the average correlation between RPS returns and the returns of the US equity market are negative. Abstracting from implementation costs, we demonstrated both analytically and empirically that these results imply that portfolios of RPS will tend to have quite high Sharpe ratios.

In regard to academics who seek to document that they have found a genuinely new RPS, we show that the probability that a randomly chosen RPS has a positive alpha after being orthogonalized against 5 (25) other randomly chosen RPS is 62 % (32 %). We interpreted this as indicating that that the returns of a potentially new RPS need to be orthogonalized against the returns of some but not all pre-existing RPS.

We conclude our study by positing that a unified model of market efficiency or inefficiency will need to be able to accommodate the new facts that we have documented about RPS—particularly the large number of RPS that exist and their generally uncorrelated return structure. We conjecture that to do this will be somewhat challenging because the existence of more than 330 RPS whose returns are not highly cross-correlated prima facie suggests that either US stock markets are pervasively inefficient or that the number of rationally priced sources of risk in equity returns for theorists to understand and explain is far larger than previously envisaged. In terms of future work, we propose that identification of the number and economic features of the subset of RPS that span the returns generated by the full set of more than 330 individual RPS is likely to be a necessary condition for both theorists and empiricists to better understand the nature of market efficiency and inefficiency.

Acknowledgments We appreciate valuable comments from Peter Algert, Suresh Govindaraj, Gilad Livne, Russell Lundholm, Jim Ohlson, Panos Patatoukas, Peter Pope, an anonymous referee, and workshop participants at City University London, the 2012 Citi Global Quant Conference, and the 2012 Review of Accounting Studies Conference. A full listing of the papers referenced in and used by this study is available from the authors on request.

Appendix: Attributes recorded in the return predictive signals (RPS) database

A. General paper attributes

- Title
- For each author:
  - Last name
  - Area (usually based on their title, e.g., Assistant Professor of Finance):
    - Accounting
    - Finance
    - Economics

    - Law
    - Other academic area
    - Practitioner

- Date published
- Journal the paper was published in, if it had been published as of Dec. 31, 2010
- Date of earliest working paper version of the paper, whether or not the paper was published. If no working paper version could be found but the paper had been published, the date of the earliest working paper version was assumed to be 24 months prior to the publication date.

B. Data used in the paper

- Time period used to analyze the signal (e.g., Apr. 1, 1986–Nov. 30, 1994)
- Last date used in analyzing the RPS in the earliest working paper (e.g., Dec. 31, 1995)
- Databases employed, a partial list of which includes the following:

    - CRSP
    - Compustat
    - I/B/E/S
    - First Call
    - CDA Spectrum and Thomson Reuters Insider Filings
    - OptionMetrics
    - SDC
    - TAQ
    - ExecuComp

- Exchanges used (NYSE, AMEX, NASDAQ, other)
- Dummy variable coding that analysis was restricted to Dec. 1 fiscal year-end firms
- Dummy variable coding that analysis excluded financial institutions

C. Return predictive signals

- General features

    - Signal name (e.g., cash flow from operations)
    - Signal definition (e.g., the particular Compustat data items and formula)
    - When calculated (e.g., once annually on May 1)
    - We include only the first paper in which a particular signal was reported. Later papers on the same signal are not included in the database.
    - In the infrequent cases in which a given paper reported results for $N > 1$ new signal, the underlying paper is entered into the database N different times.

- Return features
  - Returns are coded as positive numbers as long as the long/short sides are intuitively defined. There are a very few papers for which even after intuitively defining the long and short sides, the actual empirical mean return is negative. These usually arise in the context of robustness tests. We leave these as negative in the database.
  - Frequency over which returns are calculated
    - Daily, weekly, monthly, quarterly, yearly
  - Number of years' returns (e.g., March 1990 through June 1996 = 6.33 years)
  - Approach used to construct returns
    - Deciles, quintiles, specific (e.g., top and bottom ninth of firms ranked on the RPS), other (e.g., not taking a hedge approach but instead going long in all firms that announced a stock repurchase).
  - Weighting of returns
    - Equally weighted, value-weighted, other. We categorize returns that are calculated using criteria such as "only the largest 500 or 1,000 firms," or "the largest 10 % or 20 % of firms" as being value-weighted.
- Return performance
  - Mean return as reported in the paper. This can be the mean of a pooled time-series cross-section of returns or the mean of a time-series of (typically average) returns.
  - Sharpe ratio reported in the paper. Since this is very rarely provided by authors, where we are able we calculate it using information in the paper. However, we do this only for time-series returns, not for pooled time-series cross-sections of returns.
  - *t*-statistic reported in the paper (pooled or time-series)
  - Percentage of returns that are positive
  - Mean annualized return. We calculate this by scaling up the mean return as reported in the paper in a noncompound way. Thus, if the reported mean return reported is 1.34 % per month, we take the annualized mean return to be $1.34\,\% \times 12 = 16.08\,\%$.
  - Sharpe ratio of annualized returns. We define this as the mean annualized return divided by the standard deviation of annualized returns. We usually derive the standard deviation of annualized returns from the *t*-statistic on the reported mean return. Thus, if the reported mean return reported is 1.35 % per month based on a time-series of 15 years of monthly returns and a time-series *t*-statistic of 4.52, we take the annualized Sharpe ratio to be 4.52 divided by the square root of 15. This calculation assumes that the (in this case monthly) RPS returns are serially uncorrelated.

- When available, the performance of both equally weighted and value-weighted returns is recorded.
- A few papers report a variety of robustness results for the RPS being studied. When present, we report the average of these (e.g., the average return across the various robustness tests) to avoid data-snooping only the "best" performance.

- Firm characteristics [factor returns] used to risk-adjust returns
  - Beta [RMKT]
  - Firm size [SMB]
  - Book-to-market [HML]
  - Momentum [MOM]
  - Other

References

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance, 61*(1), 259–299.

Asness, C. S., Porter, R. B., & Stevens, R. L. (2000). Predicting stock returns using industry-relative firm characteristics. Working paper, University of Florida.

Bailey, D. H., & López de Prado, M. M. (2012). The Sharpe indifference curve. Working paper, Tudor Investment Corp.

Balakrishnan, K., Bartov, E., & Faurel, L. (2010). Post loss/profit announcement drift. *Journal of Accounting & Economics, 50*, 20–41.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, 99*(2), 427–446.

Bandyopadhyay, S. P., Huang, A. G., & Wirjanto, T. S. (2010). The accrual volatility anomaly. Working paper, University of Waterloo.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*(1), 3–18.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. Stulz (Eds.), *Handbook of the economics of finance* (pp. 1051–1121). Netherlands: Elsevier Science, B.V.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of market efficiency. *Journal of Finance, 32*, 663–682.

Bauman, W. S., & Dowen, R. (1988). Growth projections and common stock returns. *Financial Analysts Journal, 44*, 79–80.

Bazdresch, S., Belo, F., & Lin, X. (2010). Labor hiring, investment, and stock return predictability in the cross-section. Working paper, University of Minnesota.

Bernard, V. (1989). Capital markets research in accounting during the 1980's: A critical review. In T. J. Frecka (Ed.), *The state of accounting research as we enter the 1990s*. Urbana, IL: University of Illinois at Urbana-Champaign.

Brandt, M. W., Kishore, R., Santa-Clara, P., & Venkatachalam, M. (2008). *Earnings announcements are full of surprises*. Working paper, Duke University.

Brandt, M. W., Santa-Clara, P., & Valkanov, R. (2009). Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *Review of Financial Studies, 22*, 3411–3447.

Browne, D. P., & Rowe, B. (2007). The productivity premium in equity returns. Working paper, University of Wisconsin.

Chandrashekar, S., & Rao, R. K. S. (2009). The productivity of corporate cash holdings and the cross-section of expected stock returns. Working paper, University of Texas at Austin.

Chemmanur, T., & Yan, A. (2009). Advertising, attention and stock returns. Working paper, Boston College.
Chen, L., & Zhang, L. (2010). A better three-factor model that explains more anomalies. *Journal of Finance, 65*(2), 563–595.
Chordia, T., Subrahmanyam, A., & Anshuman, R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics, 59*, 3–32.
Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of asset returns. *Journal of Finance, 63*(4), 1609–1651.
Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets, 1*(2), 203–219.
DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naïve diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies, 22*(5), 1915–1953.
Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross-section of stock returns. *Journal of Finance, 57*(5), 2113–2141.
Eberhart, A. C., Maxwell, W. F., & Siddique, A. R. (2004). An examination of long-term abnormal stock returns and operating performance following R&D increases. *Journal of Finance, 59*(2), 623–650.
Frazzini, A., & Lamont, O. A. (2006). *The earnings announcement premium and trading volume*. Working paper, University of Chicago.
Gettleman, E., & Marks, J. M. (2006). Acceleration strategies. Working paper, University of Illinois at Urbana-Champaign.
Green, J., & Hand, J. R. M. (2011). The importance of accounting information in portfolio optimization. *Journal of Accounting, Auditing and Finance, 26*(1), 1–34.
Green, J., Hand, J. R. M., & Soliman, M. (2011). Going, going, gone? The demise of the accruals anomaly. *Management Science, 57*(5), 797–816.
Hafzalla, N., Lundholm, R., & Van Winkle, M. (2007). Percent accruals. *The Accounting Review, 86*(1), 209–236.
Hawkins, E. H., Chamberlain, S. C., & Daniel, W. E. (1984). Earnings expectations and security prices. *Financial Analysts Journal, 40*(5), 24–27; 30–38; 74.
Hou, K., & Robinson, D. T. (2006). Industry concentration and average stock returns. *Journal of Finance, 61*(4), 1927–1956.
Huang, A. G. (2009). The cross section of cashflow volatility and expected stock returns. *Journal of Empirical Finance, 16*(3), 409–429.
Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance, 45*, 881–898.
Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance, 48*, 65–91.
Keim, D., & Ziemba, W. (2000). *Security market imperfections in worldwide equity markets*. Cambridge: Cambridge University Press.
Kothari, S. P. (2001). Capital markets research in accounting. *Journal of Accounting and Economics, 31*, 105–231.
Lerman, A., Livnat, J., & Mendenhall, R. R. (2008). The high-volume return premium and post-earnings announcement drift. Working paper, New York University.
Lev, B., & Ohlson, J. A. (1982). Market-based empirical research in accounting: A review, interpretation, and extension. *Journal of Accounting Research, 20*(Supplement), 249–322.
McLean, R. D., & Pontiff, J. (2012). Does academic research destroy stock return predictability? Working paper, University of Alberta.
Novy-Marx, R. (2012). The other side of value: The gross profitability premium. *Journal of Financial Economics* (forthcoming).
Pontiff, J., & Woodgate, A. (2008). Share issuance and cross-sectional returns. *Journal of Finance, 63*(2), 921–945.
Rendleman, R. J., Jones, C. P., & Latané, H. A. (1982). Empirical anomalies based on unexpected earnings and the importance of risk adjustments. *Journal of Financial Economics, 10*(3), 269–287.
Richardson, S. A., Sloan, R. G., Soliman, M. T., & Tuna, I. (2005). Accrual reliability, earnings persistence and stock prices. *Journal of Accounting & Economics, 39*(3), 437–485.
Richardson, S., Tuna, I., & Wysocki, P. (2010). Accounting anomalies and fundamental analysis: A review of recent research advances. *Journal of Accounting and Economics, 50*, 410–454.
Rosenberg, B., Reid, K., & Lanstein, R. (1985). *Journal of Portfolio Management, 11*, 9–16.

Schwert, G. W. (2003). Anomalies and market efficiency. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the economics of finance* (pp. 939–974). Netherlands: Elsevier Science, B.V.

Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review, 71*(3), 289–315.

Soliman, M. T. (2008). The use of DuPont analysis by market participants. *The Accounting Review, 83*(3), 823–853.

Subrahmanyam, A. (2010). The cross-section of expected stock returns: What have we learned in the past twenty-five years of research? *European Financial Management, 16*(1), 27–42.

Thomas, J. K., & Zhang, H. (2002). Inventory changes and future returns. *Review of Accounting Studies, 7*(2–3), 163–187.

Thomas, J., & Zhang, F. X. (2011). Tax expense momentum. *Journal of Accounting Research, 49*(3), 791–821.