The Supraview of Return Predictive Signals

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Abstract

This study speaks to investment academics and practitioners by describing the population of return predictive signals (RPS) discovered and publicly identified during the period 1970-2010. Our supraview brings to light a number of new facts about RPS, including that many more RPS exist than is commonly realized (our database contains over 330 signals); the statistical properties of newly discovered RPS have remained stable over time; the returns and Sharpe ratios earned by famous RPS such as accruals and momentum are lower than those of the median RPS; and that RPS with higher mean returns also have higher Sharpe ratios. We propose that the investment performance available to practitioners from exploiting the population of RPS may be very large since empirically we estimate that the average cross-correlation between RPS returns is close to zero. We further show that because the average absolute cross-correlation between RPS returns is also low, the probability that an RPS with a significantly positive raw hedge return will have a reliably positive alpha after being orthogonalized against the market, HML, SMB, MOM and five (15) other randomly chosen RPS is 65% (43%). We interpret these results as being good news for academics and practitioners because they suggest that practitioners can expect to create value for their clients by hunting down new sources of alpha, and academics seeking to document a truly new RPS need not orthogonalize the returns of their new RPS against all pre-existing RPS. However, we note that the low average signed and absolute cross-correlations between RPS returns do present a challenge to academics because they imply that either U.S. stock markets are pervasively inefficient, or there exist a very large number of rationally priced sources of risk in equity returns for theorists to understand and explain.

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- Comments welcomed. A full listing of the papers referenced in and used by this study is available from the authors on request.

1. Introduction

In this study, we seek to inform investment academics and practitioners by reporting the results of adopting 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 of the cross-section of U.S. stock returns. We refer to such characteristics as ―return predictive signals” or RPS for short.

To the best of our knowledge, no previous academic study has sought to identify, describe and analyze the existing *population* of RPS. Rather, scholarly research into RPS has centered on discovering and reporting the identity and properties of new signals, typically in the form of one RPS per paper. In contrast to this approach, we demonstrate that taking the supraview of RPS brings to light novel facts that both enrich and challenge academic understanding, and provide practitioners with information they may be able to use to improve their investment performance. As such, we view our paper as taking an initial step of response to the call made by Richardson, Tuna and Wysocki (2010) that researchers in the RPS area begin to move away from what Richardson et al. describe as ―the haphazard nature of this line of research” and instead move toward imposing more structure on the extant anomalies literature. The structure we seek to contribute through our paper is a description of the population of RPS, which we propose is a necessary, though certainly not sufficient, condition for future progress to be made in and by the empirical and theoretical wings of academic RPS research.

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 years 1970-2010. Using our database, we uncover a number of surprising new facts about RPS.

Our first finding is that there are far more RPS than is commonly realized. Our database alone contains 330 different signals, over six times the number reported by Subrahmanyam (2010) and vastly more than the ‗classic‘ size, book-to-market, momentum, and beta firm characteristics or their factor returns HML, SMB, MOM and RMKT. Despite this prevalence of publicly reported RPS, we observe that 88% of RPS papers orthogonalize returns against only one or more of the highly limited subset of RPS that consists of RMKT, SMB/size, HML/book-to-market, and MOM/momentum.

Second, we statistically describe the return properties of the population of RPS and key subdivisions thereof. 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 the underlying published or working papers) are 12.1%, 12.1% and 1.04, respectively (n = 239). In contrast, 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 show that RPS returns outperform the US equity market—the annual excess returns on the CRPS equally-weighted (value-weighted) market over the same time periods as those used by the academics in the first paper on a given RPS are only 9.5% and 0.50 (6.6% and 0.44). Moreover, 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 standard deviation of returns. We note too that the mean returns, standard deviations of returns and Sharpe ratios of accounting-based RPS are very similar to those of finance-based RPS, and that, both accounting- and finance-based RPS perform better than do other-based RPS.

Our third supralevel finding pertains to the discoverers of RPS. Namely, that while accounting faculty dominate in the discovery of accounting-based RPS and finance faculty dominate in finance-based RPS, finance faculty discover more accounting-based RPS than the converse. This runs counter to the commonly held presumption that accounting academics are more engaged in finance research than are finance academics engaged in accounting research. Practitioners, usually as coauthors, account for just 7% of academically discovered RPS.

Fourth, we show that the mean returns and Sharpe ratios earned by famous RPS such as accruals and momentum are smaller than those of the median RPS. For example, Sloan reports that his accruals signal 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. Jegadeesh and Titman‘s momentum signal (defined as 6-month lagged returns with a holding period of 6 months) displays a mean equally-weighted annualized return of 11.4% and a Sharpe ratio of 0.61, whereas the median finance-based RPS has a mean equally-weighted annualized return of 11.9% and a Sharpe ratio of 0.98.

Fifth, we document that the mean returns, standard deviations of returns and Sharpe ratios of newly discovered RPS remain quite stable over time. RPS discovered in 2000s do not have reliably different return properties to RPS discovered in the 1990s, 1980s or 1970s.

Sixth, we show that while RPS with higher mean returns are riskier in the sense that they have larger time-series standard deviations of returns, they also manifest higher Sharpe ratios. We argue that the latter finding is surprising because if market prices are set by sophisticated investors, and the returns from RPS represent the rewards to sophisticated investors from making uncertain investments into discovering new signals, then RPS with higher mean returns should arguably have lower, not higher Sharpe ratios. Our reasoning is that since sophisticated investors already hold highly diversified portfolios, they should primarily rank investments into the discovery of new signals by the expected Sharpe ratios of those new signals, not by the level or standard deviation of the projected returns (Bailey and López de Prado, 2012). Given this, and given that levering a diversified portfolio is costly (Asness, Frazzini and Pedersen, 2012), we argue that equilibrium in the domain of RPS discovery predicts a negative relation between the returns expected from newly discovered RPS and their Sharpe ratios because otherwise there would be no economic tradeoff present in the discovery of RPS. Stated differently, a negative relation between the expected returns of newly discovered RPS and their Sharpe ratios is consistent with low expected return / high Sharpe ratio RPS being as attractive to sophisticated investors as high expected return / low Sharpe ratio RPS, because although low expected return / high Sharpe ratio RPS offer higher Sharpe ratios than high expected return / low Sharpe ratio RPS, their inclusion into a sophisticated investor‘s portfolio requires costly leverage, diminishing their benefits on a net-of-leverage-costs basis.

Lastly, we explore the investment performance that is potentially available to practitioners in our RPS population database. Using the analytical approach of Bailey and López de Prado (2012), we show that while the expected Sharpe ratio of any single equally-weighted RPS is 1.0, the Sharpe ratio of a portfolio built from the population of RPS can theoretically exceed 3.0. However, achieving such a large Sharpe ratio depends crucially on the average cross-correlation between RPS returns being very small, on the order of 0.1 or less. This leads us to conclude that there is substantial economic value to be gained by academics and/or practitioners empirically measuring the full set of cross-correlations between RPS returns, especially for practitioners with low execution costs.

Given the enormous time and expense involved in measuring all 54,285 of the return cross-correlations for our database of 330 RPS, we instead estimate the population average cross-correlation by sampling 33 signals that a-priori we judge to be easy to program from CRSP, Compustat and I/B/E/S, and for which reasonably complete data is available during the 30-year period 1981-2010. We find that the average cross-correlation of raw returns for our sample of 33 signals is only 0.06 when hedge returns are equally-weighted in the top and bottom deciles of signal strength and 0.07 when hedge returns are value-weighted. The magnitudes of these average cross-correlations confirm that there may be sizeable investment performance available to practitioners who can exploit the population of existing RPS with low execution costs.

We further show that because the average absolute cross-correlation between RPS returns in our sample of 33 signals is also low (less than 0.25), the probability that a given RPS with a significantly positive raw hedge return will also have a reliably positive alpha after being orthogonalized against the market, HML, SMB, MOM and five (10, 15) other randomly chosen RPS is about 65% (54%, 43%). We propose that this finding is good news for both academics and practitioners because it suggests that practitioners can expect to add value to their investment strategies by hunting for new sources of alpha, and that academics who uncover what they think are truly new RPS may reasonably not need (or be required) to orthogonalize the returns of the new RPS against the returns from every single pre-existing RPS. We further speculate that editors who have published papers on RPS may perhaps be able to breathe easier because our results suggest that controlling for even 15 randomly chosen pre-existing RPS beyond the market, HML, SMB and MOM, it is far certain that the inference made by the author that his/her proposed new signal is academically unique would be overturned.

Despite these items of good news, however, we also propose that the very low average cross-correlation and the relatively low average absolute cross-correlation between the population of RPS returns is bad news for academics. The reason is that the presence of 330 RPS whose returns are at worst only weakly correlated with each other implies that either U.S. 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 (Cochrane, 2011).

The remainder of our study proceeds as follows. In section 2 we describe the construction of the RPS database, and in section 3 we report and in places seek to explain the new findings that emerge from analyzing the database. In section 4 we analyze the mean-variance investment performance that might be optimally extracted by investment practitioners from the population of RPS discovered by academics. We conclude the paper in section 5.

2. RPS database

We construct our database of the population of return predictive signals discovered and publicly disclosed by accounting, finance and other business faculty by searching the 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 we included in the database. We also searched for working papers about RPS posted 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 code into the database only the first paper about an RPS (the RPS paper).[1]

We categorize each RPS as accounting-based, finance-based, or other-based. An accounting-based RPS is one where the signal is in the firm‘s financial statements (e.g., accruals; cash flows; assets). A finance-based RPS is one where 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. Other-based signals are those that are neither accounting nor finance, 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 Appendix A, although not every paper has 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 paper was published (if published by 12/31/2010), the date of the first publicly available version of the paper (typically on SSRN, and if not on SSRN, defined to be two years prior to the date of publication), the databases the study drew on (CRPS, Compustat, etc.), the name and definition of the signal(s), the period over which the signal(s) was/were analyzed, whether the returns from the signal(s) is/are computed on an equally-weighted or value-weighted basis, the firm characteristics or factor returns that signal returns are orthogonalized against, and key aspects of signal performance—most notably the annualized mean return(s) and annualized Sharpe ratio(s).

[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 (2000), 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 describing the return properties of that population.

3. New facts about RPS made visible by taking a supraview

Our RPS database, containing as it does an approximation of the population of publicly disclosed return predictive signals, enables us to detect, measure and report several new supra or "forest-level" facts about RPS that we will argue are of value to both academics and practitioners. In this section we describe these new facts and seek 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 333 RPS is evidence that far more RPS exist than is commonly presumed. For example, the number of RPS we identify is 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 79 are other-based.

In Figure 1 we graph the cumulative number of RPS discovered and publicly reported by business academics. Panel A shows the cumulative number of each type of RPS, while panel B plots the natural log of one plus the cumulative number of RPS. Both panels reveal that the discovery of RPS has grown exponentially over time. Moreover, all three of the accounting-based, finance-based and other-based RPS series suggest that as of December 2010, the growth in the discovery of new RPS had shown no sign of diminishing.

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 that RPS papers have been published in. 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. However, a finance faculty member is almost three times as likely to be an author or coauthor on a paper that discovers an accounting-based RPS than is an accounting faculty member to be an author or coauthor on a finance-based RPS paper (35% vs. 13%). This runs counter to the view that is sometimes promulgated that accounting academics are more engaged in finance research than the other way around. Beyond accounting and finance faculty, economics and law faculty account for only a tiny fraction of RPS papers, and practitioners are authors on just 7% of RPS papers.

The relative density of sole versus joint authorship on RPS papers is similar across accounting-based, finance-based and 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 return predictive signal studied, 99% of RPS papers use CRPS stock returns and 74% employ the Compustat database. One reason for the intense use of Compustat is that beyond accounting-based RPS per se, a large number of finance-based and other-based papers orthogonalize returns against book-to-market, and calculate firms‘ book values from Compustat. Beyond CRPS 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 non-traditional databases such as the NBER patent database, Google searches, Execucomp, Moodys, Dow Jones News Retrieval service, and many others.

We note that RPS papers 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 to 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 How returns are measured in RPS papers

RPS papers use one of three main methods to identify new signals that are predictive of future stock returns: regressions, event studies, and hedge portfolios. Of the 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 or is not efficiently priced by the market.[2] In contrast, most event studies and virtually all hedge portfolio papers are focused on estimating the returns that could (on paper) be earned by trading on the signal.

In the regression approach, the researcher includes her signal of interest X_{it} 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 usually pooled time-series cross-sectional in nature, and aimed at determining whether the estimated coefficient on the publicly available X_{it} is reliably non-zero and thereby 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 the event study approach, RPS returns are created by effectively taking long-only or short-only (but not

[2] The exception in regression studies occurs when the independent signal variable is in decile ranks, since in this case the estimated coefficient on the signal is the return to a zero-investment portfolio optimally formed to exploit the signal and returns (Abarbanell and Bushee, 1998).

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 how long the stock is held for 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 twenty years, and 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_t, 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 for after long/short positions are taken, how long the strategy is implemented for, 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 all RPS combined 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. From Panel B, when grouping firms based on signal sorts, 38% group firms into deciles or something akin to deciles, while 31% group based on quintiles, tertiles, or above/below the median value. A majority (57%) of other-based RPS use no grouping because they use the event-study, 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 showing that of the 91% of RPS papers that orthogonalize their raw RPS returns against at least one risk factor or firm-specific characteristic, only 12% orthogonalize against something other than one or more of RMKT, SMB/size, HML/book-to-market, and MOM. This contrasts with the 48% of academic respondents to the survey sent by Richardson, Tuna and Wysocki (2010, table 1, Q1) who in answer to the question ―Which risk model is most appropriate for risk calibration of an equity trading strategy?" replied either the Fame-French 3-factor model plus other factors, or a model outside of the mainstream. This contrast, taken together with the sheer number of RPS that our database confirms have been reported into the public domain, raises the question of why researchers who propose that they have discovered a new RPS would choose to orthogonalize against so few risk factors or firm characteristics?

One possibility is that researchers intensively focus their energies on documenting one new RPS per paper (the trees), and are therefore unaware of the huge number of RPS that exist (the forest) and against which they might need to be orthogonalizing the returns of their one newly discovered RPS. Another possibility is that researchers do appreciate that a huge number of RPS exist, but believe (without empirically-based evidence) that controlling for some or all of the huge library of RPS will not change the inference that the signal they are focusing on truly represents a new RPS. A third and more speculative possibility may be that researchers are concerned that if they were to orthogonalize against more RPS, then the probability that their particular RPS would remain incrementally predictive and thus be publishable would fall. If so, then their economic incentive to take the (substantial, perhaps even prohibitive) amount of time to comprehensively orthogonalize their RPS against the library of existing RPS is small.

3.4.2 How we redefine and standardize RPS returns

Since return holding periods vary from one day to one year in RPS studies (Table 3, panel C), we standardize reported mean returns by annualizing. We do so by simply multiplying daily mean returns by 250, weekly mean returns by 52, monthly mean returns by 12, quarterly mean returns by 4, and semi-annual mean returns by 2. Since astonishingly few RPS papers report Sharpe ratios, for RPS papers where a time-series of mean RPS returns are reported, we 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 Documenting the return performance of the population of RPS

For the first time in the RPS literature, the forest level 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 number of new facts, several of which we suggest are somewhat surprising and unexpected.

In our description of the return properties of RPS, we separate equally-weighted returns (Table 4) from value-weighted returns (Table 5). Each of Tables 4 and 5 displays 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 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 dollar-neutral, they do not include the risk-free return that in reality would be earned on the short-sale proceeds posted as collateral with the stock lenders—viz., the short rebate.[4] Rather than add the risk-free return to the figures in Panels A-D, we subtract the one-month risk-free rate from market returns in arriving at Panel E. On a pre-transactions cost, pre-fees basis, Panel E therefore enables us to compare the naïve

[3] We set aside 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.

[4] We note that in reality there is no such thing as a zero net-investment portfolio. A dollar-neutral investment requires underlying capital (Jacobs and Levy, 2005). Also, while we recognize that the short rebate is usually divided between the stock lenders, the prime broker, and the investor, for simplicity we assume that the full amount of the short rebate accrues to the investor.

baseline investing approach of going long in the RPS versus going long in the market.[5] Inspection of Panel A in Tables 4 and 5 reveals the following noteworthy results.

3.4 New facts about RPS

3.4.1 The number of, and weighting methods used in, RPS

First, of the total of 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 section 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.

3.4.2 Mean RPS returns

Second, 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 at 12.2% is 4.1% higher than the mean annualized value-weighted RPS return of 8.1% (Table 4, Panel A versus Table 5, Panel A). We note that the mean equally-weighted of 12.2% is very close to the stylized “ideal hedge fund” 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 assist in making 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).[6]

Third, 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, Panel B

[5] The two investing approaches are naïve because RPS returns and excess market returns are essentially uncorrelated. Hence a linear combination of the two approaches would dominate either one separately.

[6] 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.

vs. Panel C, and Table 5, Panel B vs. Panel 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).

3.4.3 RPS Sharpe ratios

The fourth 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 were 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 than 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.

3.4.4 Returns of famous RPS relative to returns of all RPS taken together

Fifth, we document the somewhat surprising result that the returns and Sharpe ratios earned by famous RPS such as the post-earnings announcement drift, accruals, book-to-market, firm size and momentum are below those of the median RPS. 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]

3.4.5 Calendar time evolution of the properties of RPS returns

Sixth, 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

[7] Jegadeesh and Titman (1993) actually 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 six 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 six month lagged-RPS in our supraview database, not all 32 RPS.

ratios of newly discovered RPS do not materially change over time.[8] Said differently, RPS discovered in the 2001-2010 decade do not have materially higher or lower returns or Sharpe ratios to RPS discovered in the 1990s, 1980s or 1970s.

We illustrate this in Figure 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). Newly discovered RPS as a whole are in panel A, accounting-based RPS are in panel B, finance-based RPS are in panel C, and other-based RPS are in panel D. Underneath each panel we report the t-statistics pertaining to the estimated slope coefficients in regressions of mean annualized EW and VW RPS returns on the year in which the RPS was first reported. None of the t-statistics are significant at the 5% level in a two-tailed test, confirming the purely visual indications 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 found in Figures 3 and 4, where we plot the annualized standard deviations of RPS returns and the Sharpe ratios of both equally-weighted and value-weighted mean returns by the year in which the paper that first discovered the RPS was made publicly available. Across Figures 2 and 3 combined, only one of the 16 t-statistics is significantly different from zero, statistically confirming absence of reliable calendar time trends in the standard deviations and Sharpe ratios of the returns of newly discovered RPS.

Based on the evidence reported in Figures 2-4, we conjecture that the discovery of RPS by business academics is ‗pure' in the sense that it is appears to be undertaken without regard to the value of the discovered RPS to investors. We suggest that if the discovery of new RPS by academics was driven by their potential value to investors, then we would expect that not only would there would be far fewer than 330 published RPS papers, but that those RPS with the largest (smallest) returns and Sharpe ratios would tend to be discovered early on (later on) in the 1970s (2000s). We further conjecture that the reason that the academic discovery of RPS is pure is because academics value the fruits of being a tenured professor—high and nonvolatile pay, a great degree of intellectual freedom, having no direct boss, and strong work/life balance—more than they value the fruits of what they could plausibly achieve elsewhere, such as the far higher

[8] We cannot identify working papers before the advent of SSRN. For published papers where 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.

but more volatile pay, lesser degree of intellectual freedom, being under the authority of a boss, and the weak work/life balance associated with being a senior executive such as a Managing Director at a top investment bank.

3.4.6 The riskiness of RPS considered individually versus from a portfolio perspective

The seventh and penultimate new result that we uncover from our taking the forest level or 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. These relations can be seen in Figures 5 and 6, respectively. Of the eight estimated slope coefficients in regressions of mean RPS returns on their associated standard deviations of returns shown in panels A-D of Figure 5, seven are significantly positive, and of the eight estimated slope coefficients in regressions of mean RPS returns on their associated Sharpe ratios shown in panels A-D of Figure 6, all eight are significantly positive.

We argue that while the former result is intuitively appealing, the latter result is surprising because if market prices are set by sophisticated investors, and the returns from RPS represent the rewards to sophisticated market participants from making uncertain investments into the discovery of new signals, then RPS with higher mean returns would be expected to have lower, not higher Sharpe ratios. The reasoning that leads us to this view is that sophisticated investors already hold highly diversified portfolios, against which RPS returns are presumably relatively uncorrelated. As such, they will rank investments into the discovery of new signals by the expected Sharpe ratios of those new signals, not by the level or standard deviation of the projected returns (Bailey and López de Prado, 2012).[9]

Given this, and given that leveraging a portfolio is both costly and risky (Asness, Frazzini and Pedersen, 2012), then equilibrium in the area of RPS discovery would predict the presence of a negative relation between the returns expected from newly discovered RPS and their Sharpe ratios, because otherwise there would be no economic tradeoff present in the discovery of RPS. Stated differently, a negative relation between the expected returns of newly discovered RPS and their Sharpe ratios is consistent with low expected return / high Sharpe ratio RPS being as

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[9] 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." Mr. Lopez de Prado is Head of Global Quantitative Research at Tudor Investment Corp., which as of August 2011 had a reported $11 billion of assets under management.

attractive to sophisticated investors as high expected return / low Sharpe ratio RPS, because although low expected return / high Sharpe ratio RPS offer higher Sharpe ratios than high expected return / low Sharpe ratio RPS, their inclusion into a sophisticated investor's portfolio requires costly leverage, diminishing their benefits on a net-of-leverage-costs basis.

3.4.7 Return properties of academic RPS versus practitioner RPS

A further result we uncover is that the RPS that large sophisticated practitioners publicly report using appears to be a truncated subset of the RPS population. We show this in Figure 7, where in panel A we repeat Figure 6 panel A that displays the mean returns of academically reported RPS versus their Sharpe ratios, but where in panel B we show the mean RPS returns and Sharpe ratios that J.P. Morgan report in their US Factor Reference Book (dated 1/27/11).[10]

A visual comparison of panels A and B of Figure 7 clearly shows that the RPS that J.P Morgan report in their US Factor Reference Book have a maximum Sharpe ratio of 1.1, regardless of whether implementation of the RPS are restricted to large-cap firms 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.

There are several potential explanations for the truncated RPS set reported by J.P. Morgan. The first, and we believe the least likely, is that large sophisticated practitioners such as J.P. Morgan are unaware of academically discovered RPS that have Sharpe ratios above 1.1. A second and more likely explanation is that J.P. Morgan deliberately restricts itself to a much smaller investable universe than the typical academic study (e.g., the Russell 3000 rather than all CRSP firms regardless of their market cap). Third, it might be that the academic RPS that report Sharpe ratios larger than 1.1 only do so because they inadvertently reflect data mining on the part of the researchers. Fourth, it may be that J.P. Morgan is fully aware of the population or RPS, but chooses not to publicly reveal that they make the RPS population available to their clients. The fifth and final possibility that warrants consideration is that J.P. Morgan does know about the population of RPS and their return properties, but does not tell its clients about academically discovered RPS with Sharpe ratios above 1.1 because it uses such RPS only for investing its own capital and/or that of its partners, not that of its clients.

[10] While J.P. Morgan is clearly but one of a large number of sophisticated investors in the equity markets, we argue that there is no a priori reason to suppose that they are a biased proxy for all sophisticated equity investors.

4. Implications of adopting an RPS supraview

4.1 Potential of improved investment performance for practitioners

An obvious question to pose in light of the 330 RPS that we document have been discovered and reported by business academics in the past 40 years is the degree to which the RPS can be optimally used to improve the investment performance of a sophisticated investor's U.S. equity portfolio, or the U.S. equity component of a worldwide, multi-asset portfolio.

We seek to provide answers to this question by using the algebraic machinery described in Bailey and López de Prado (2012, hereafter BLP) and then plugging into BLP's analytics the estimates of the key parameters involved that we obtain from our RPS database.

BLP calculate that if that the returns of S return predictive signals are described by:

$$r_s \sim N(\mu_s, \sigma_s^2), \text{ for } s = 1, \dots, S \tag{1}$$

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:

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

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 $\bar{\rho} = \frac{2\sum_{s=1}^{S}\sum_{s=s+1}^{S}\rho_{s,t}}{S(S-1)}$ is the average correlation of RPS returns across the off-diagonal elements in the variance-covariance matrix.

A key attraction of the equal volatility weighting scheme used by BLP is that it allows for the Sharpe ratio SR_p of a set of RPS to be succinctly described by just three parameters: the number of RPS, the average Sharpe ratio of the RPS, and the average cross-correlation between the RPS.[11] Within this framework, equation (3) also reveals that SR_p is a linear function of $\overline{SR}$ and a convex function of S and $\bar{\rho}$.

[11] Bailey and López de Prado 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, Garlappi and Uppal (2009), who compare 14 models of optimal

We apply equation (3) to our RPS database in two steps. In the first step, we arrive at theoretical indications of the relations between SR_p and S, $\overline{SR}$ and $\bar{\rho}$ by fixing $\overline{SR}$ at its empirical value, then analytically varying S and $\bar{\rho}$. In the second step, we empirically estimate $\bar{\rho}$ using a sample of 33 readily programmed signals from our database of the population of RPS.

The theoretical results for equally-weighted RPS are shown in Figure 8. Panel A reports $\overline{SR}$ as a function of S for varying levels of $\bar{\rho}$, given that the mean Sharpe ratio of the n = 208 RPS that report a Sharpe ratio is 1.04 (Table 4, panel A). Panel B of Figure 8 reports $\overline{SR}$ as a function of $\bar{\rho}$ 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 $\bar{\rho}$. For example, when $\overline{SR} = 1.04$, the Sharpe ratios achieved when $S = 5$ are 1.08 when $\bar{\rho} = 0.9$, 1.19 when $\bar{\rho} = 0.7$, 1.34 when $\bar{\rho} = 0.5$, 1.57 when $\bar{\rho} = 0.3$, 1.97 when $\bar{\rho} = 0.1$, and 2.12 when $\bar{\rho} = 0.05$. If instead $S = 330$ (more than a sixtyfold increase in S), the Sharpe ratios obtained are 1.10 when $\bar{\rho} = 0.9$, 1.24 when $\bar{\rho} = 0.7$, 1.47 when $\bar{\rho} = 0.5$, 1.89 when $\bar{\rho} = 0.3$, 3.24 when $\bar{\rho} = 0.1$, and 4.52 when $\bar{\rho} = 0.05$. Panel B makes the same point in a slightly different way, by showing that Sharpe ratios increase as S increases, but at a decreasing rate, while Sharpe ratios increase as $\bar{\rho}$ decreases, but at an increasing rate.

Given the enormous time and expense required to estimate $\bar{\rho}$ by programming and measuring all 54,285 of the return cross-correlations in our RPS database, we instead seek to empirically translate the theoretical results reported in Figure 8 by sampling 33 signals that we judged to be readily programmable using CRSP, Compustat and I/B/E/S, and for which reasonably complete data is available during the 30-year period 1981-2010.[12] The 33 signals we select are shown in Table 6. Of the signals, 24 are accounting-based, 7 are finance-based, and 3 are other-based. For each signal, and for both equally- and value-weighted returns, we compute the mean annualized return and the annualized Sharpe ratio and report these in the rightmost two columns. Each signal is operationalized such that the sign of the expected hedge return is positive. Of the 33 signals, 25 (18) have significantly positive mean equally-weighted (value-

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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.

[12] Of the 33 signals, 29 have returns for the maximum 360 months. The remaining four signals have a mean of 286 months of data available.

weighted) returns and for these signals the mean annual hedge return is 12.7% (8.7%), the mean t-statistic is 6.0 (3.0), and the mean Sharpe ratio is 1.09 (0.54).[13]

In Table 7 we report the Pearson (above the diagonal) and Spearman (below the diagonal) cross-correlations of the monthly returns of the RPS subset listed in Table 6, where equally-weighted returns are used in panel A and value-weighted returns in panel B. Inspection of Table 7 indicates that many cross-correlations are surprisingly small. For example, the Pearson correlation between the monthly returns from Sloan‘s (1996) accruals signal and Hafzalla, Lundholm and Van Winkle‘s (2007) percent accruals signal is just 0.25 for equally-weighted returns and 0.04 for value-weighted returns.

Table 8 aggregates the individual correlations shown in Table 7 by reporting the average cross-correlations (panel A) and average absolute cross-correlations (panel B) of the monthly RPS returns. Each panel reports statistics using equally-weighted and value-weighted returns, the full set of 33 signals and the subset of signals for which the associated mean return t-statistics exceed 1.96, and the subperiods 1981-1990, 1991-2000, 2001-201 as well as the full period 1981-2010. We compute the average absolute cross-correlation in addition to the average signed cross-correlation because the former will enable us to determine if there are many or few highly negative as well as highly positive individual cross-correlations that would not be detectable from computing just the latter. We compute statistics for the full set of 33 signals and the subset of signals for which the associated t-statistics exceed 1.96 to address the potential concern that it may be that cross-correlations between signals that have significantly positive mean returns and signals that do not will be lower than the cross-correlations between only signals that have significantly positive mean returns.

Table 8 panel A indicates that the average cross-correlation between the monthly returns in our approximately 10% sample of the underlying RPS population is very small. For the full sample period 1981-2010, the average cross-correlations range between 0.03 and 0.07, depending on whether all 33 signals are included or signals with a t-statistic < 1.96 are excluded, and whether equally-weighted or value-weighted returns are chosen. Moreover, Table 8 shows that the average cross-correlations are relatively stable over time, being similar across 1981-1990, 1991-2000 and 2001-2010.

[13] For the sake of keeping our paper focused, we choose to finesse the very valid question of why 7 of the 33 signals have neither a positive mean equally-weighted return nor a positive mean value-weighted return, given that the original academic papers reported positive mean hedge returns to the signals involved.

Taking the cross-correlations reported in panel A of Table 8 as unbiased estimates of the mean signed cross-correlations of the population of RPS returns allows us to map out and report in Figure 9 the empirical relation between the number of RPS in an equal volatility weighted portfolio of RPS signals and the expected Sharpe ratio of that portfolio. In constructing the curves reported in Figure 9, we simply plug into equation (3) the following parameter estimates. For equally-weighted returns, from Table 4 panel A we take $\overline{SR} = 1.04$ and from Table 8 panel A we take $\bar{\rho} = 0.06$; and for value-weighted returns, from Table 5 panel A we take $\overline{SR} = 0.70$ and from Table 8 panel A we take $\bar{\rho} = 0.07$. These trace out the two curves seen in Figure 9.

Figure 9 clearly reveals the potentially large gains in U.S. equity investment performance available to practitioners who are able to avail themselves of multiple RPS (especially at low transactions costs), rather than just one or two RPS. Specifically, we estimate that for equally-weighted returns the expected Sharpe ratio of a portfolio of 15 RPS drawn from our RPS database is 2.97 versus 1.04 for a single RPS. As additional RPS are added, the expected portfolio Sharpe ratio increases at a decreasing rate such that with 300 RPS in the portfolio, the RPS portfolio reaches 4.15. The parallel results for value-weighted returns are less spectacular, but nonetheless impressive, with the expected Sharpe ratio of a portfolio of 15 RPS hitting 1.93 versus 0.70 for a single RPS. With 300 RPS in the value-weighted return portfolio, the RPS portfolio achieves a Sharpe ratio of 2.59.

4.2 Academic confidence in concluding that a newly discovered RPS is truly novel

It is tempting to infer from the all but zero average signed cross-correlations reported in Table 8 that academics who discover what they believe is a truly novel RPS no longer need to orthogonalize the returns of their new RPS against the returns of any or all pre-existing RPS. However, this would be incorrect because a zero average cross-correlation could hide the presence of signals whose returns are very highly negatively and/or very highly positively correlated with those of the new RPS.

Although qualitatively we note that the average absolute cross-correlations reported in panel B of Table 8 appear to be fairly small, ranging between 0.18 and 0.24 depending on whether all 33 signals are included or signals with a t-statistic < 1.96 are excluded and whether equally-weighted or value-weighted returns are chosen, it is impossible to state with confidence whether absolute cross-correlations of this magnitude do or do not obviate the need on a researcher's part to orthogonalize his/her RPS returns against those of any or all preexisting RPS.

We therefore provide quantitative evidence on this topic in the following manner, where without loss of generality we describe our process based on using equally-weighted RPS returns. First, we restrict ourselves to the subset of the 33 RPS that have significantly positive mean returns. Second, from this subset, we randomly select a single RPS. Third, we randomly select one other RPS in the subset, and regress the returns of the first randomly selected RPS on the market return, HML, SMB, MOM, and the returns of the other randomly selected RPS, and note whether the estimated intercept is significant at the 5% level. Fourth, we repeat the second and third steps 500 times. Then we measure the percentage of the 500 repetitions that result in a significant intercept. Fifth, we repeat steps two through four but in step three we randomly select two other RPS in the subset; then on completion of that, we repeat by randomly selecting three other RPS, etc. This process then yields the percentage of times that a randomly drawn RPS and N randomly drawn other RPS (plus the 4 base factors) results in a significant intercept.

We graphically report the resulting percentages in Figure 10, where the x-axis varies the number of the randomly selected N factors used to explain the returns to a given randomly selected RPS. Figure 10 shows that selecting a single additional explanatory factor (N = 1) results in an approximately 85% probability that a selected signal is judged significant. This probability declines to 65% when N = 5, 54% when N = 10, and 43% when N = 15.

We interpret this evidence as being good news for academics who uncover what they think are truly new RPS, because Figure 10 indicates that researchers may reasonably not need (or be required) to orthogonalize the returns of the new RPS against the returns from every single pre-existing RPS. We further speculate that editors who have published papers on RPS may perhaps be able to breathe easier because our results suggest that controlling for even controlling for 15 randomly chosen pre-existing RPS beyond the market, HML, SMB and MOM, it is far certain that the inference made by the author that his/her proposed new signal is academically unique would be overturned.

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 returns in US stock markets. Rather than seek to discover new RPS, our approach has been to describe and analyze an approximation of the population of RPS that has already been discovered. In doing so, we seek to take an initial step of response to the call made by Richardson, Tuna and Wysocki (2010) that researchers in the RPS area begin to move away from what Richardson et al. describe as ―the haphazard nature of this line of research" and instead move toward imposing more structure on the extant anomalies literature. The structure we seek to contribute through our paper is a robust description of the population of RPS across a variety of financial and nonfinancial dimensions.

Through our supraview, we uncover a variety of new facts about RPS. These include the observations that many more RPS been identified than is commonly realized; the statistical properties of newly discovered RPS have remained stable over time; the returns and Sharpe ratios earned by famous RPS such as accruals and momentum are lower than those of the median RPS; and 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.

We also argued that the investment performance available to practitioners from exploiting the population of RPS may be large because we estimate that the average cross-correlation between RPS returns is close to zero. We further showed that since the average absolute cross-correlation between RPS returns is also fairly small (less than 0.25), the probability that a newly discovered RPS with a significantly positive raw hedge return will have a reliably positive alpha after being orthogonalized against the market, SMB, HML, MOM and ten randomly chosen other RPS is over 50%.

We argued that our findings are good news for practitioners and academics in that they suggest that practitioners can expect to add value to their investment strategies by hunting for new sources of alpha, and that academics who discover new RPS may not need to orthogonalize the returns of their new RPS against the returns of every other pre-existing RPS. On the other hand, we also suggested that our findings are bad news for academics because they imply that either U.S. stock markets are pervasively inefficient, or that there are an enormous number of rationally priced sources of risk in equity returns for theorists to understand and explain.

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Appendix A

The attributes recorded in the return predictive signals (RPS) database

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A. The paper per se

- 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 12/31/2010
- Date of earliest working paper version of the paper, whether the paper had been published or not. If no working paper version could be found but the paper had been published, the date of the earliest working paper version was taken to be 24 months prior to the publication date.

B. Data used in the paper

- Time period used to analyze the signal (e.g., 4/1/86 - 11/30/94)
- Last date used in analyzing the RPS in the earliest working paper (e.g., 12/31/95)
- Databases employed, a partial list of which includes:
  - CRPS
  - 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 12/31 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 a year on 5/1)

- 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 that a given paper reported results for N > 1 new signal, the underlying paper is entered into the database N different times.

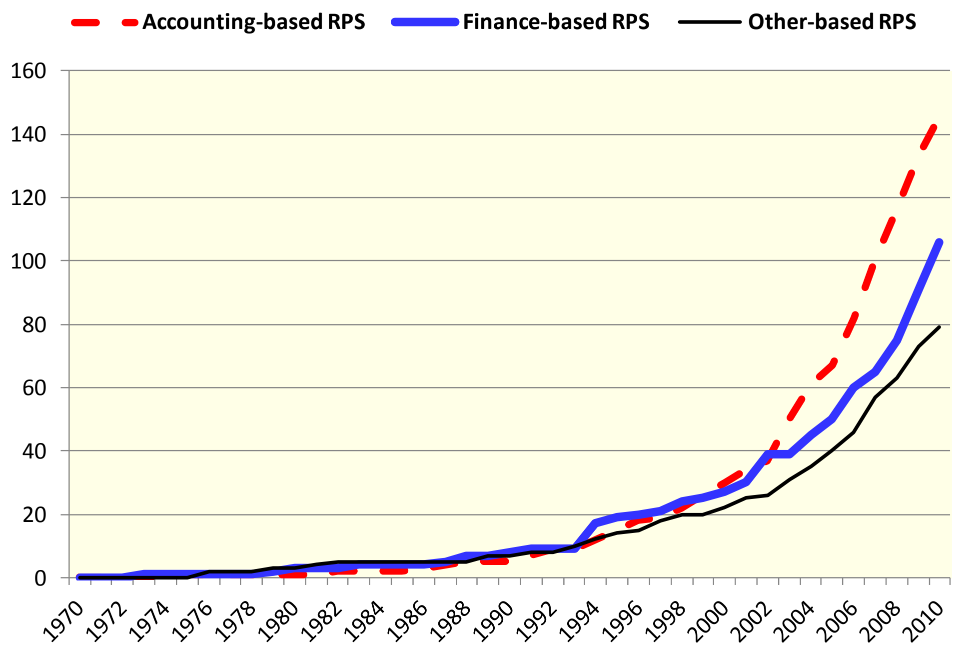
- Return features
  - Returns are coded as positive numbers as long as the long/short sides are intuitively defined. There are a very few papers for which even after intuitively defining the long and short sides, the actual empirical mean return is negative. These usually arise in the context of robustness 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 thru 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 say all firms that announced a stock repurchase).
  - Weighting of returns
    - Equally-weighted, value-weighted, other. We categorize returns calculated on 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 only do this for time-series returns, not for pooled time-series cross-sections of returns.
  - t-statistic reported in the paper (pooled or time-series)
  - Percent of returns that are positive
  - Mean annualized return. We calculate this by scaling up the mean return as reported in the paper in a non-compound way. Thus, if the reported mean return reported is 1.35% per month, we take the annualized mean return to be 1.34% x 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

FIGURE 1

Graphs displaying the cumulative number of return predictive signals (RPS) discovered by accounting, finance and other business academics, 1970-2010.

Panel A: Cumulative number of RPS



Panel B: Ln (1 + cumulative number of RPS)

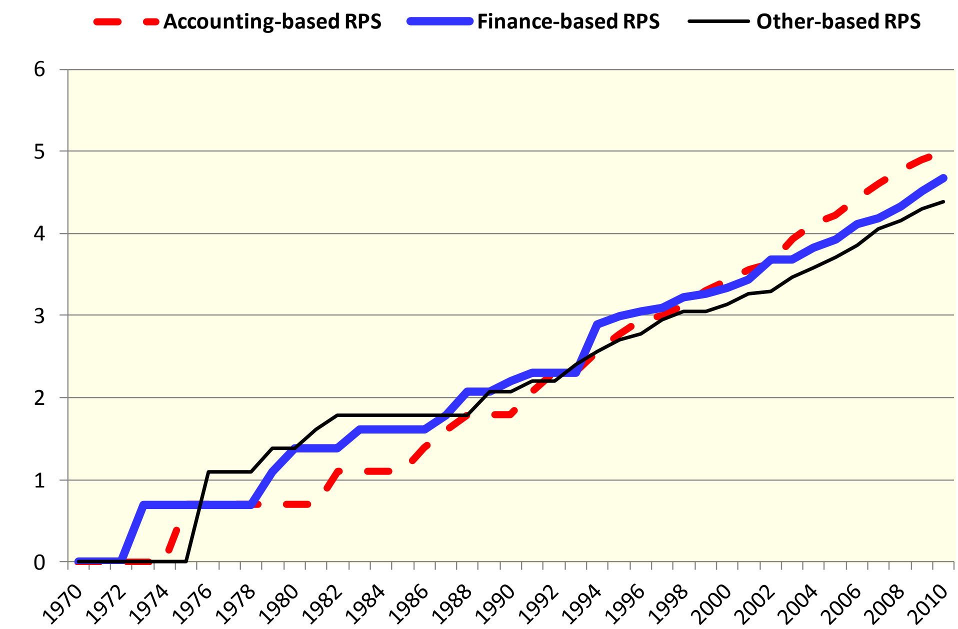
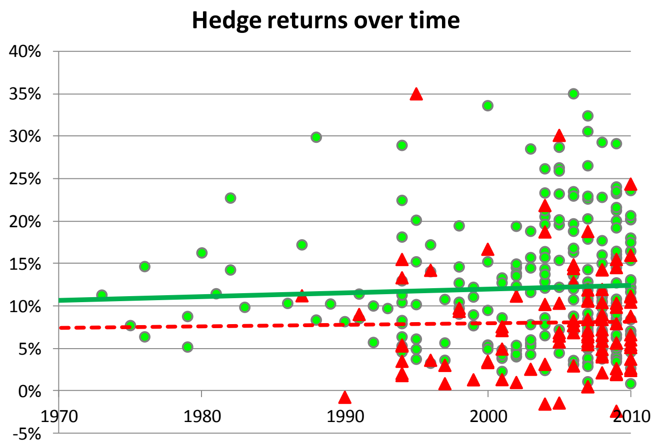
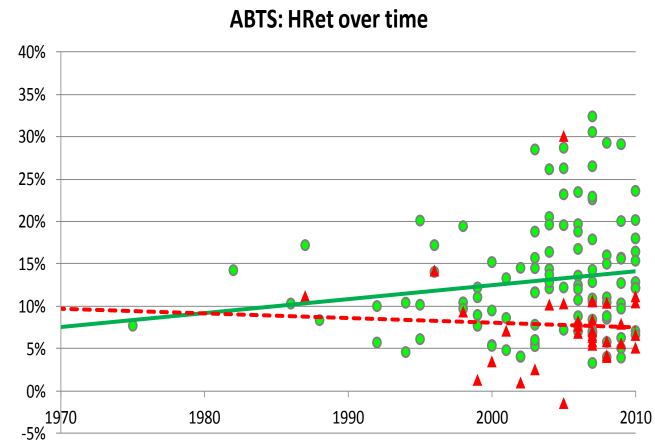


FIGURE 2

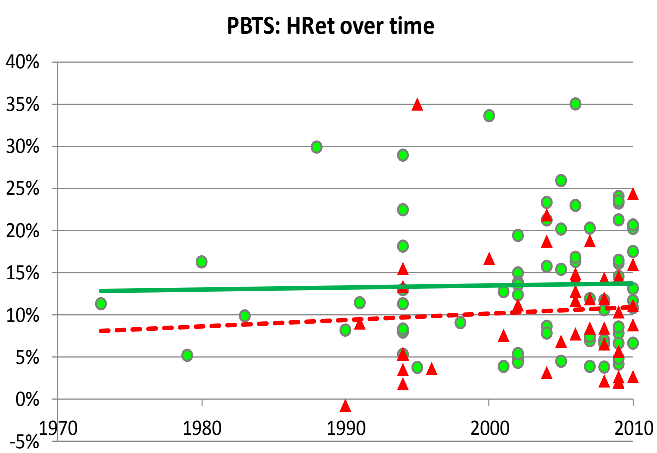
Mean annualized returns earned by return predictive signals (RPS) plotted according the year in which the RPS was first publicly reported, 1970-2010. Green (red) denotes equally-weighted EW (value-weighted VW) RPS returns. T-statistics pertain to the estimated slope coefficient in a regression of mean annualized RPS returns on the year in which the RPS was first reported.



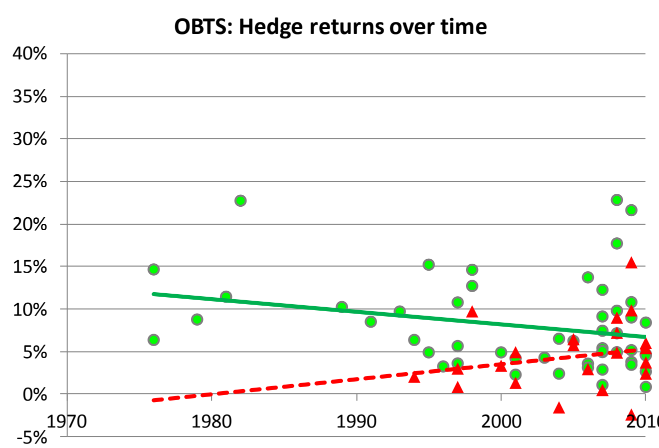
t-statistic [EW RPS] = 0.7
t-statistic [VW RPS] = 0.2



t-statistic [EW RPS] = 1.6
t-statistic [VW RPS] = –0.3



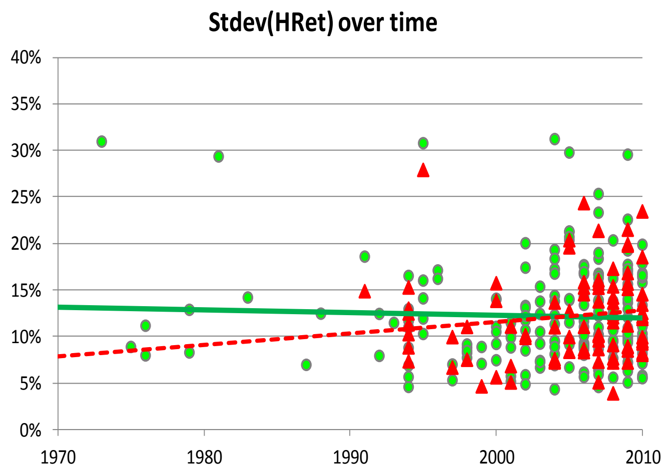
t-statistic [VW RPS] = 0.4



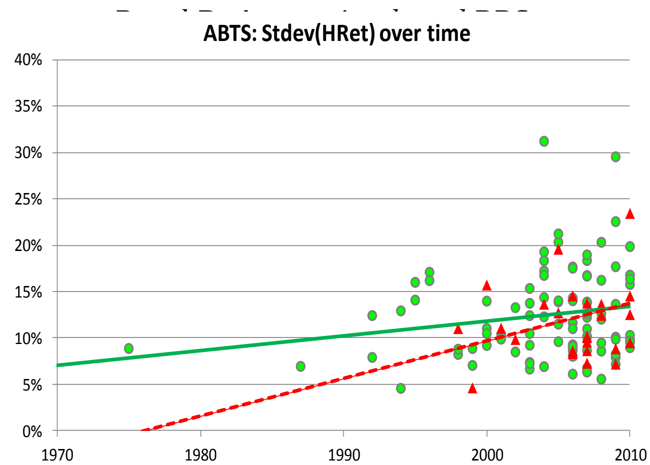
t-statistic [EW RPS] = –1.9
t-statistic [VW RPS] = 1.0

FIGURE 3

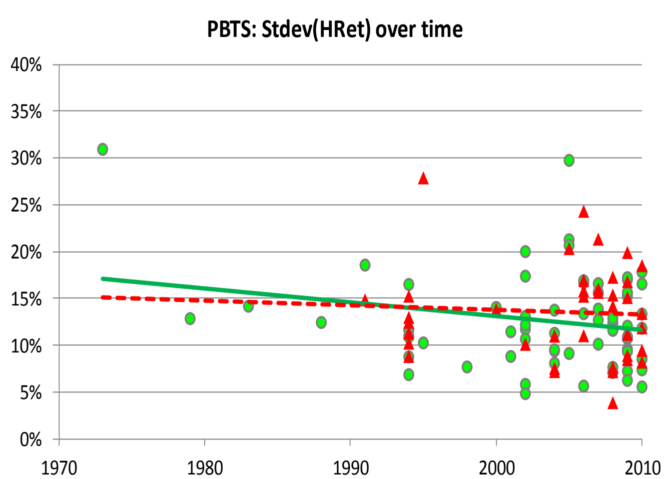
Annualized standard deviations of the returns earned by return predictive signals (RPS) plotted according to the year in which the RPS was first reported, 1970-2010. Green (red) denotes the standard deviations of equally-weighted EW (value-weighted VW) RPS returns. T-statistics pertain to the estimated slope coefficient in a regression of annualized standard deviations of RPS returns on the year in which the RPS was first reported.



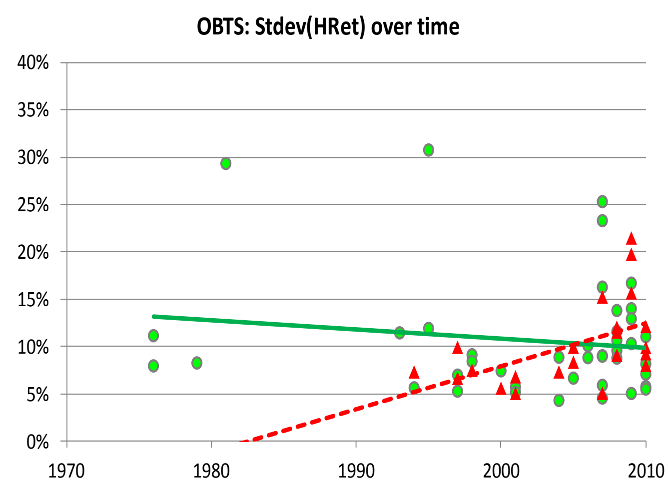
t-statistic [EW RPS] = –0.6
t-statistic [VW RPS] = 1.2



t-statistic [EW RPS] = 1.8
t-statistic [VW RPS] = 1.5



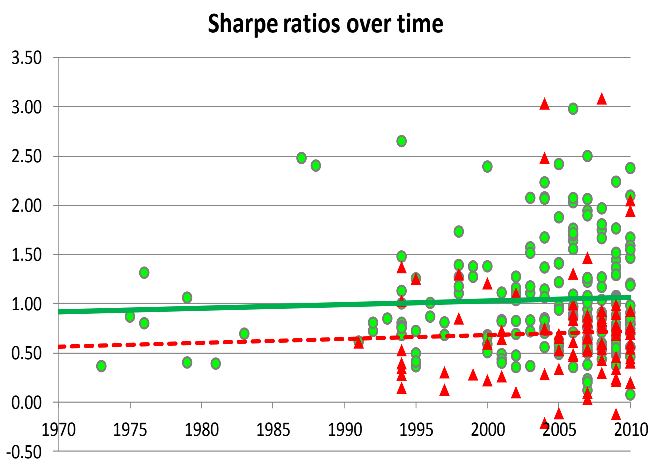
t-statistic [EW RPS] = –1.8
t-statistic [VW RPS] = –0.4



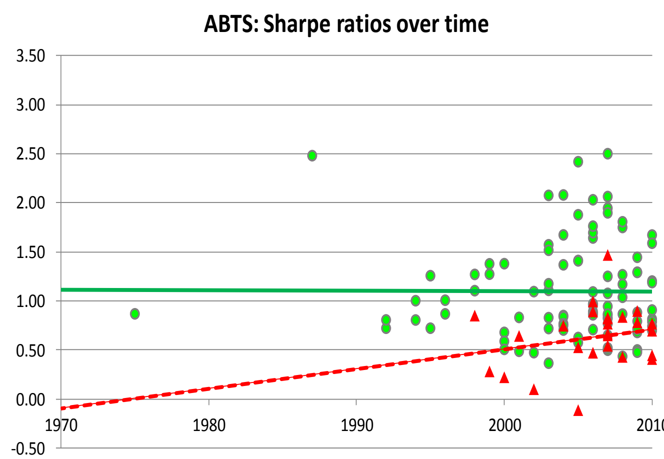
t-statistic [EW RPS] = –0.9
t-statistic [VW RPS] = 2.7

FIGURE 4

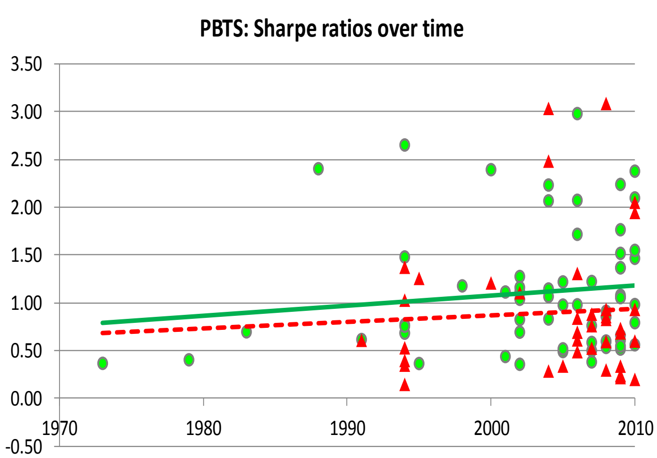
Annualized Sharpe ratios of the returns earned by return predictive signals (RPS) plotted according to the year in which the RPS was first reported, 1970-2010. Green (red) denotes the Sharpe ratios of equally-weighted EW (value-weighted VW) RPS returns. T-statistics pertain to the estimated slope coefficient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



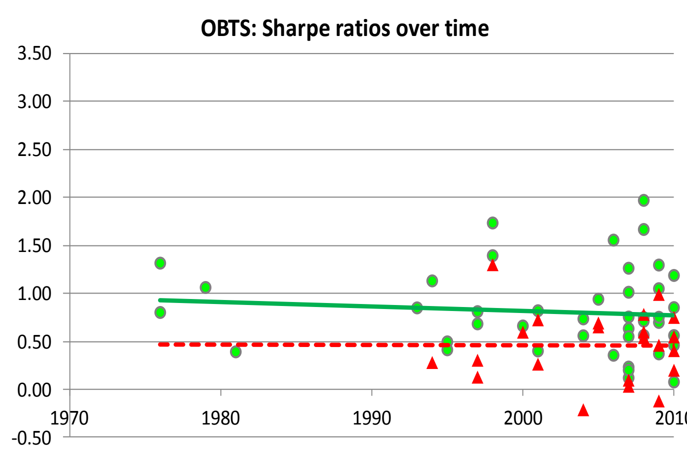
t-statistic [EW RPS] = 0.7
t-statistic [VW RPS] = 0.3



t-statistic [EW RPS] = –0.1
t-statistic [VW RPS] = 1.1



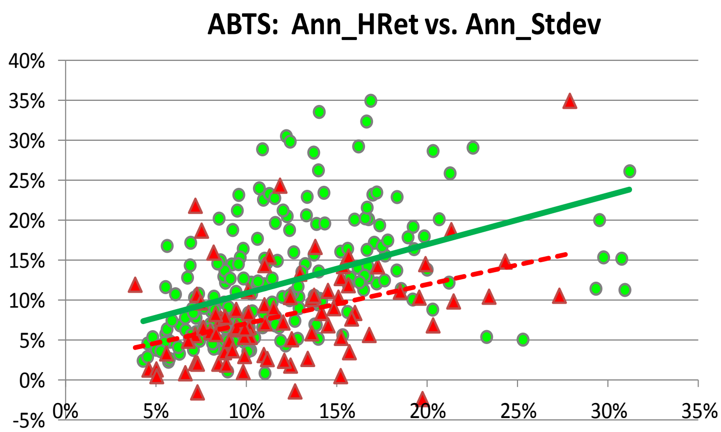
t-statistic [VW RPS] = 0.3

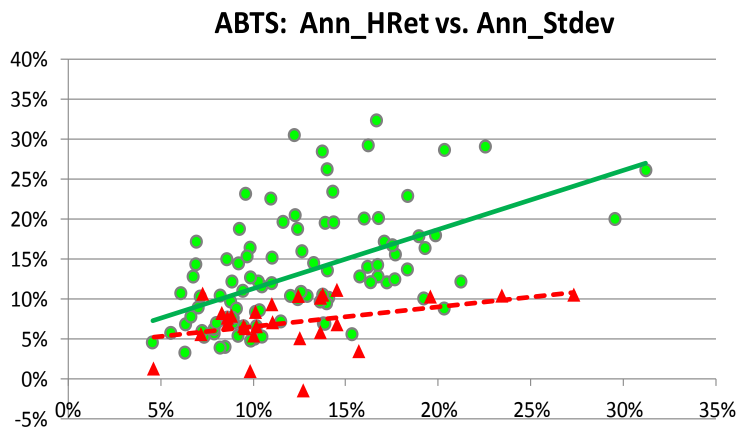


t-statistic [EW RPS] = –0.6
t-statistic [VW RPS] = –0.0

FIGURE 5

Mean annualized returns earned by return predictive signals (RPS) plotted according to the annualized standard deviations of those returns for RPS first reported during 1970-2010. Green (red) denotes equally-weighted (value-weighted) RPS returns.



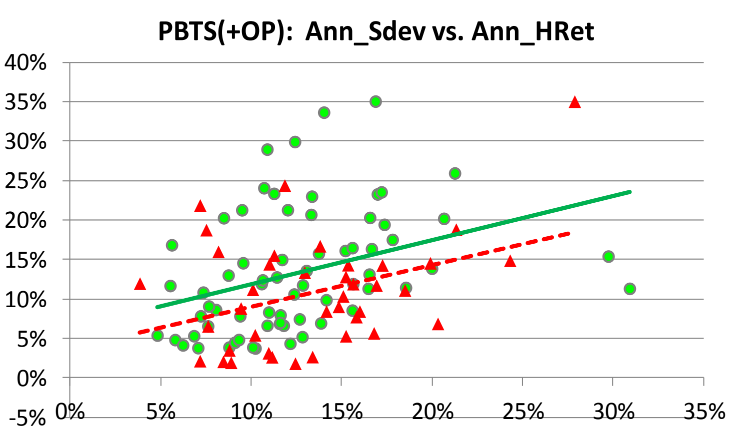


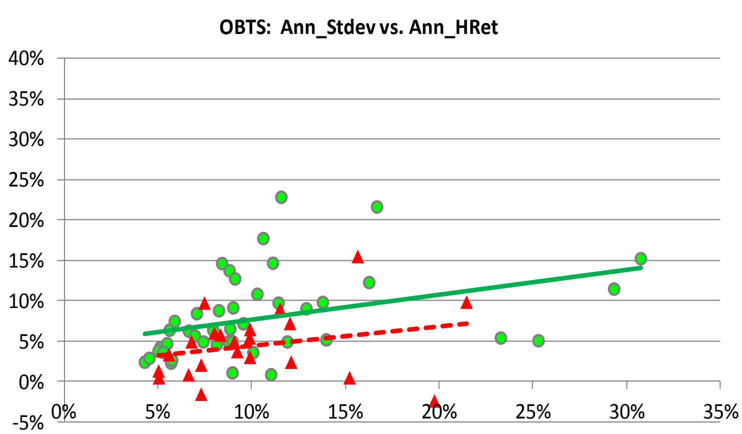
(4.2) (7.3)

$\mu[\text{Ret\_RPS\_VW}] = 2.1\% + 0.49\ \sigma[\text{Ret\_RPS\_VW}]$
(1.3) (4.1)

(2.4) (6.1)

$\mu[\text{Ret\_RPS\_VW}] = 4.2\% + 0.24\ \sigma[\text{Ret\_RPS\_VW}]$
(2.6) (2.0)





$\mu[\text{Ret\_RPS\_EW}] = 6.2\% + 0.56\ \sigma[\text{Ret\_RPS\_EW}]$
(2.6) (3.2)

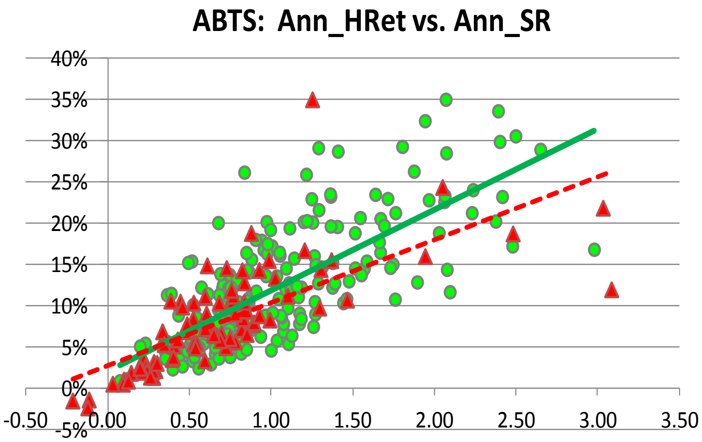
$\mu[\text{Ret\_RPS\_VW}] = 3.8\% + 0.53\ \sigma[\text{Ret\_RPS\_VW}]$
(1.2) (2.5)

$\mu[\text{Ret\_RPS\_EW}] = 4.6\% + 0.31\ \sigma[\text{Ret\_RPS\_EW}]$
(3.1) (2.5)

$\mu[\text{Ret\_RPS\_VW}] = 2.0\% + 0.24\ \sigma[\text{Ret\_RPS\_VW}]$
(0.9) (1.2)

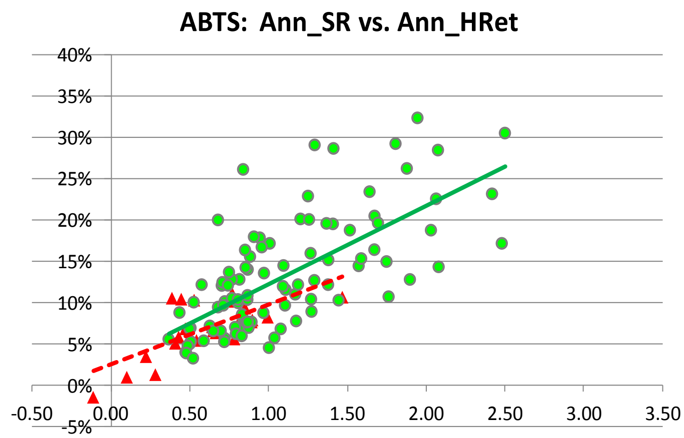
FIGURE 6

Mean annualized returns earned by return predictive signals (RPS) plotted according to the annualized Sharpe ratios (SR) of those returns for RPS first reported during 1970-2010. Green (red) denotes equally-weighted (value-weighted) RPS returns.



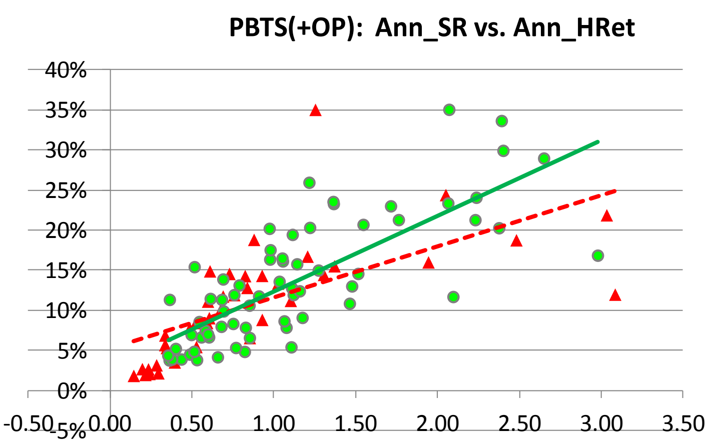
(2.8) (16.1)

μ[Ret_RPS_VW] = 2.7% + 0.08 SR[Ret_RPS_VW]
(3.9) (9.8)



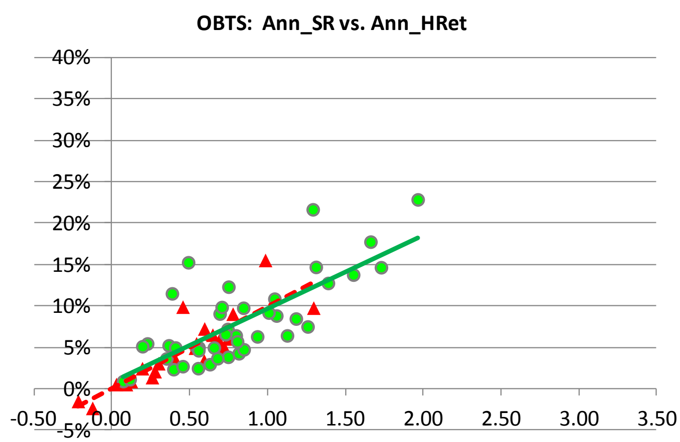
μ[Ret_RPS_EW] = 2.8% + 0.09 SR[Ret_RPS_EW]
(2.3) (9.3)

μ[Ret_RPS_VW] = 2.7% + 0.07 SR[Ret_RPS_VW]
(2.5) (4.9)



μ[Ret_RPS_EW] = 3.0% + 0.09 SR[Ret_RPS_EW]
(2.5) (9.8)

μ[Ret_RPS_VW] = 5.1% + 0.06 SR[Ret_RPS_VW]
(3.6) (5.3)



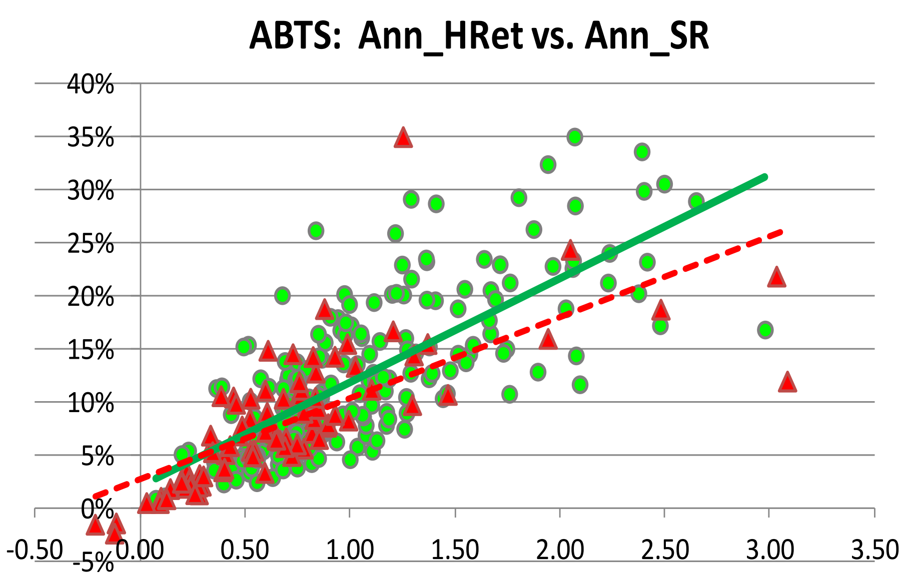
μ[Ret_RPS_EW] = 0.7% + 0.09 SR[Ret_RPS_EW]
(0.6) (7.4)

μ[Ret_RPS_VW] = 0.0% + 0.10 SR[Ret_RPS_VW]
(–0.1) (7.7)

FIGURE 7

The annualized mean returns earned by academic and non-academic return predictive signals (RPS) plotted against their annualized Sharpe ratios. RPS discovered by academics between 1970-2010 are shown in Panel A, while the RPS reported by and defined in J.P. Morgan's US Factor Reference Book dated 1/27/11 are shown in Panel B. The returns and Sharpe ratios in Panel A are taken from the underlying academic paper and do not necessarily represent the performance of the signal during 1995-2010, while those in Panel B are always for the Russell 3000 during 1995-2010. In Panel A, green (red) denotes mean returns and Sharpe ratios based on equally-weighted (value-weighted) RPS.

)



Panel B: *n, 1/27/11)*

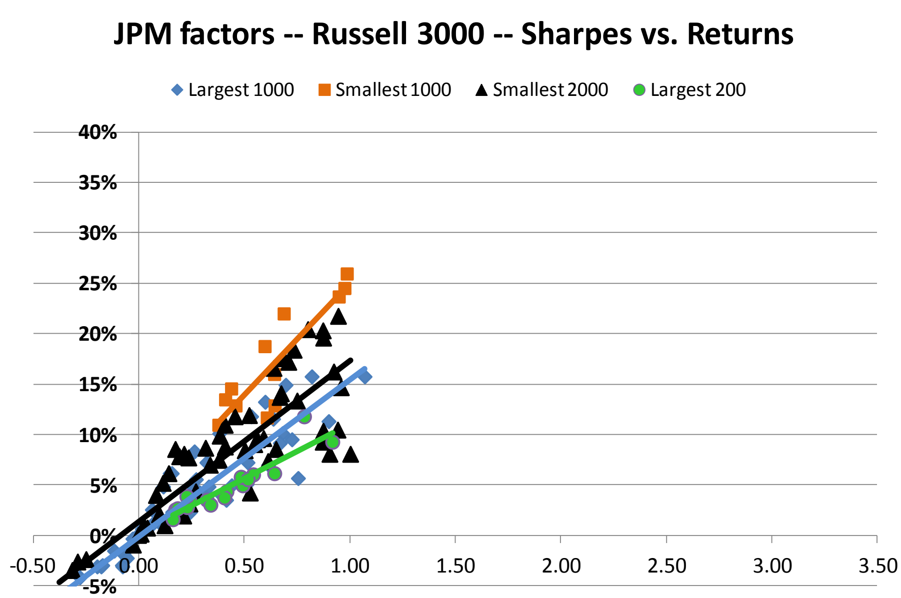
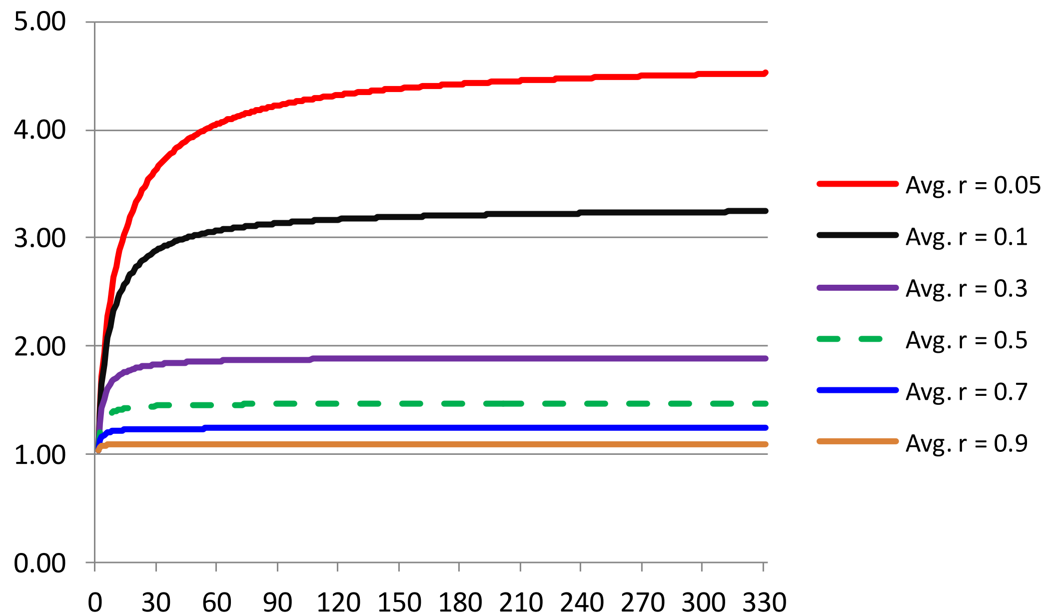


FIGURE 8

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

Panel A: Portfolio Sharpe ratios as a function of the number of RPS in the portfolio, for varying levels of average cross-correlations between RPS returns



Panel B: Portfolio Sharpe ratios as a function of the average cross-correlations between RPS returns, for varying numbers of RPS in the portfolio

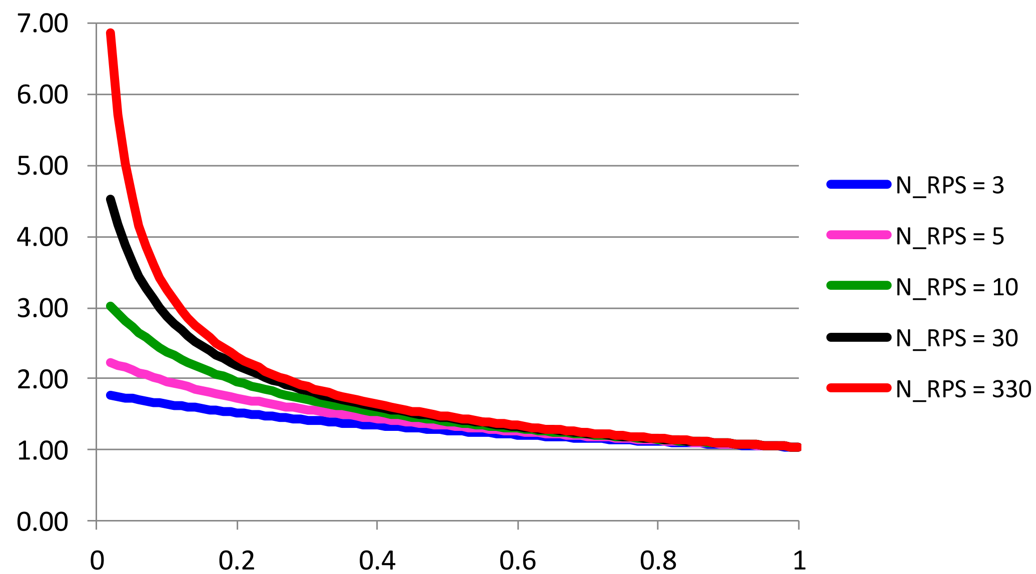


FIGURE 9

Expected Sharpe ratio of a portfolio of RPS as an empirical function of [1] the number of RPS in the portfolio and [2] estimated average cross-correlations between RPS returns per panel A of Table 8. The expected Sharpe ratios below assume a mean Sharpe ratio of 1.04 for equally-weighted RPS returns and a mean Sharpe ratio of 0.70 for value-weighted RPS returns, per panels A of Tables 4 and 5, respectively.

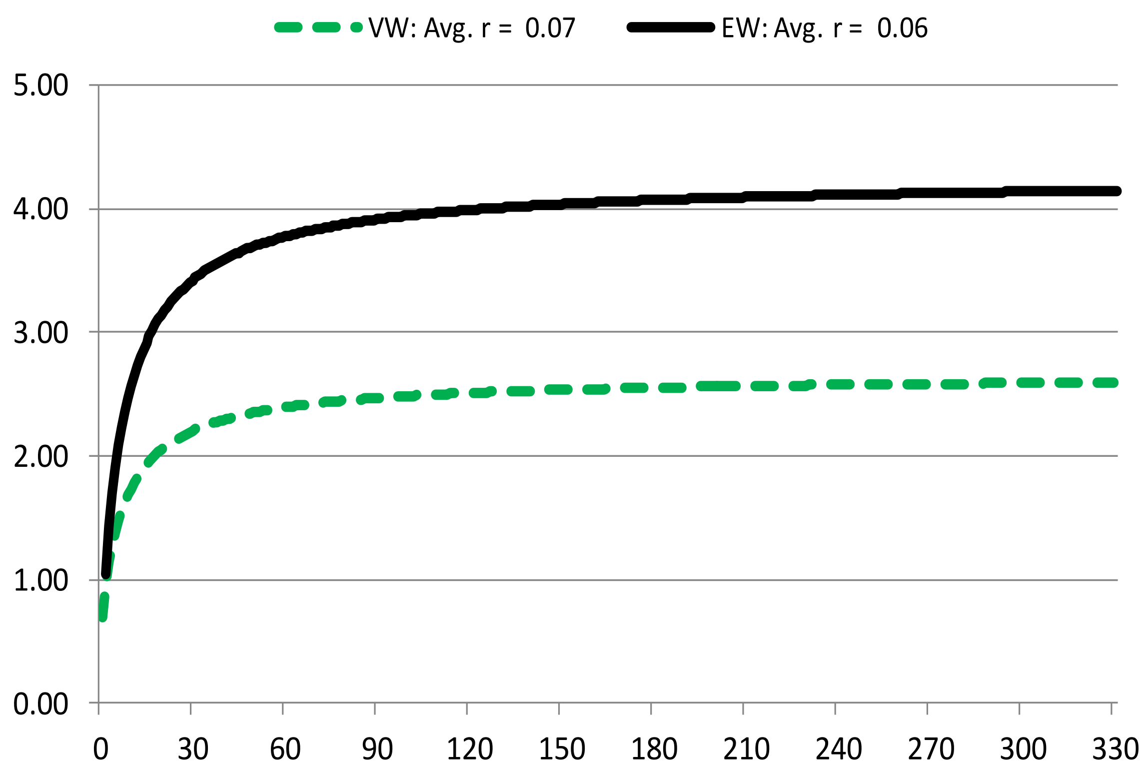


FIGURE 10

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 market return, SMB, HML, MOM and the hedge returns of up to 15 other randomly chosen RPS. The group of RPS used in this analysis is the subset of the 33 readily programmed RPS described in Table 6 for which the mean raw RPS hedge return is significantly positive. Results using equally-weighted (value-weighted) RPS returns are show in the solid red (dashed blue) line.

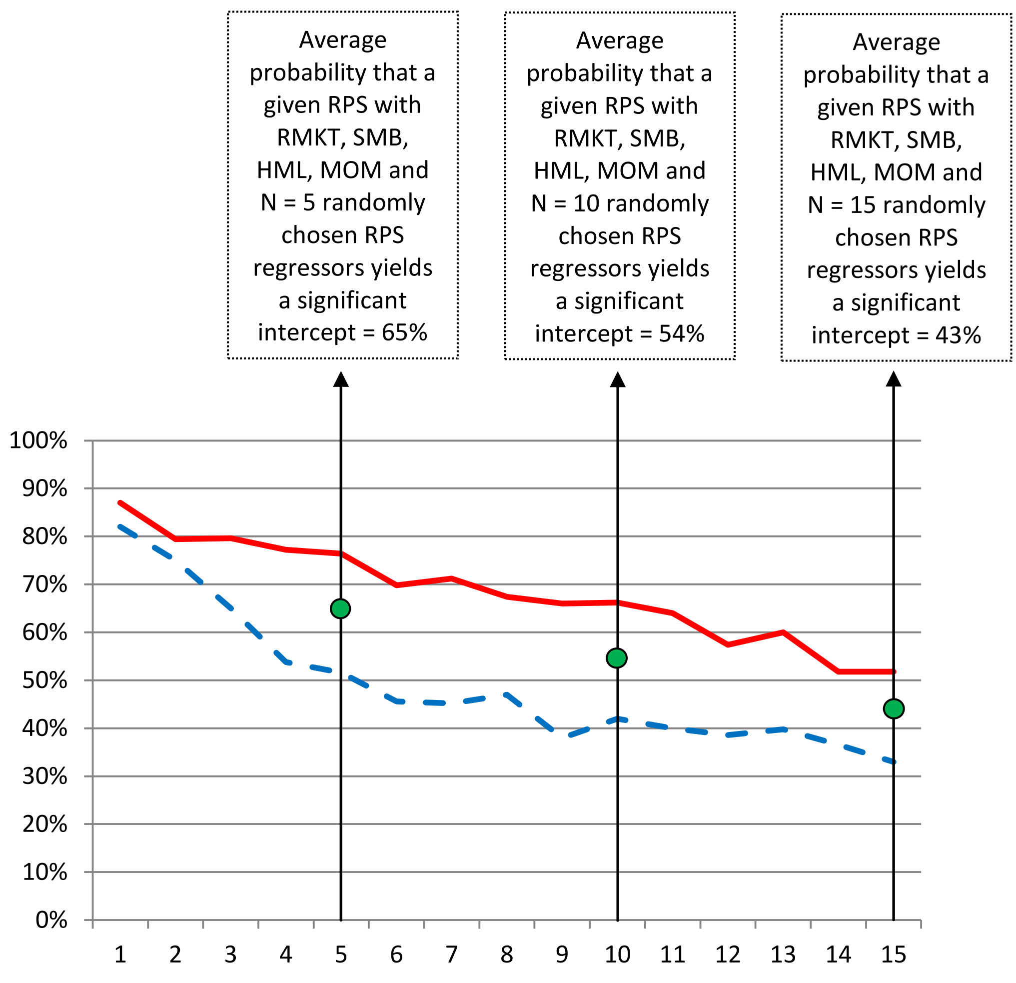


TABLE 1

Descriptive statistics regarding the authors of return predictive signal (RPS) papers and the journals that RPS papers have been published in, 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	29
Three	49	35	30
≥ Four	12	13	3
	148	107	79

Panel B: 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 & Economics	7	0	1
Review of Accounting Studies	2	0	0
Journal of Accounting, Auditing & 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 & 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 @ 12/31/10	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

		Type of RPS		
Database	All papers	Accounting	Finance	Other
CRPS	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 12/31 FYEs	4%	8%	0%	0%
Financial firms excluded	25%	44%	5%	0%

TABLE 3

Descriptive statistics on how the returns reported in RPS papers are measured, 1970-2010

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

		Type of RPS		
# sample months	All papers	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

		Type of RPS		
Portfolio grouping	All papers	Accounting	Finance	Other
< 10%	8%	9%	9%	6%
10% to 19%	38%	53%	29%	18%
20% to 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

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

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

		Type of RPS		
Signal recalculated	All papers	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%

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

	Panel A: All types of RPS			*Panel B: Accounting-based RPS*		
	Mean	Std. dev.	Sharpe	Mean	Std. dev.	Sharpe
Min.	0.8%	4.3%	0.08	3.3%	4.6%	0.37
25th percentile	6.6%	8.6%	0.68	8.5%	9.2%	0.72
Median	10.8%	11.0%	0.87	12.0%	11.5%	0.91
Mean	12.2%	12.1%	1.04	13.2%	12.4%	1.10
75th percentile	16.1%	14.3%	1.29	17.4%	16.7%	1.38
Max.	35.0%	31.2%	2.98	32.4%	31.2%	2.50
Std. dev.	7.1%	5.2%	0.55	6.9%	4.9%	0.97
Skewness	0.9	1.3	1.0	0.9	1.2	0.9
Number of RPS	237	208	208	115	97	97

	Panel C: Finance-based RPS			*Panel D: Other-based RPS*		
	Mean	Std. dev.	Sharpe	Mean	Std. dev.	Sharpe
Min.	3.7%	4.8%	0.35	0.8%	4.8%	0.35
25th percentile	6.6%	9.4%	0.61	4.3%	6.8%	0.52
Median	11.9%	11.8%	0.98	6.4%	9.0%	0.75
Mean	13.5%	12.6%	1.11	8.1%	10.6%	0.81
75th percentile	16.9%	14.4%	1.30	10.6%	11.5%	1.05
Max.	35.0%	30.9%	2.98	22.8%	30.8%	1.97
Std. dev.	7.6%	5.0%	0.63	5.4%	6.2%	0.44
Skewness	0.8	1.3	1.1	1.2	1.9	0.7
Number of RPS	72	68	68	50	43	43

Panel E: Equally-weighted market returns over the same RPS intervals (all types of RPS)

	Mean	Std. dev.	Sharpe
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
Std. dev.	2.6%	1.8%	0.15
Skewness	-0.4	-0.3	0.5
Number of RPS	333	333	333

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

Panel A: All types of RPS

	Mean	Std. dev.	Sharpe
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
Std. dev.	6.3%	5.0%	0.58
Skewness	1.4	1.0	2.1
Number of RPS	99	87	87

Panel B: Accounting-based RPS

	Mean	Std. dev.	Sharpe
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
Std. dev.	5.3%	4.9%	0.31
Skewness	2.0	1.5	0.0
Number of RPS	35	27	27

Panel C: Finance-based RPS

	Mean	Std. dev.	Sharpe
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
Std. dev.	7.1%	4.8%	0.63
Skewness	1.1	0.7	1.7
Number of RPS	42	39	39

Panel D: Other-based RPS

	Mean	Std. dev.	Sharpe
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
Std. dev.	4.1%	4.4%	0.36
Skewness	0.8	1.3	0.2
Number of RPS	23	22	22

Panel E: Value-weighted market returns over the same RPS intervals (all types of RPS)

	Mean	Std. dev.	Sharpe
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
Std. dev.	2.4%	1.3%	0.18
Skewness	-1.2	-2.3	0.6
Number of RPS	333	333	333

TABLE 6

Key descriptors of the chosen set of 33 readily programmed RPS from our database of the population of RPS. Each RPS is implemented in such a way that it generates a positive expected mean long/short hedge return.

#	Author(s)	Paper title	Signal	Signal acronym and definition	Date, Journal	Mean EW annualized return (Sharpe)	Mean VW annualized return (Sharpe)
	--	--	Market	CRSP EW or VW	--	13.3% (0.44)	11.6% (0.40)
1	Banz	The relationship between return and market value of common stocks.	Firm size	mve = market capitalization at fiscal year end	1981, JFE	14.3% (0.72)	12.0% (0.61)
2	Rosenberg, Reid & Lanstein	Persuasive evidence of market inefficiency.	Book-to-market	bm = common share holder equity book value / mve	1985, JPM	18.4% (1.31)	11.7% (0.61)
3	Jegadeesh	Evidence of predictable behavior of security prices.	12 month momentum	m12m	1990, JF	–2.9% (–0.09)	11.2% (0.31)
4	Jegadeesh & Titman	Returns to buying winners and selling losers: Implications for stock market efficiency.	One month momentum	m1m	1993, JF	29.4% (1.18)	13.8% (0.50)
5	Gettleman & Marks	Acceleration strategies.	Change in 6 month momentum	Δm = m6m – m6m_l1	2006, WP	9.3% (0.56)	9.9% (0.46)
6	Cooper, Gulen & Schill	Asset growth and the cross-section of stock returns.	Asset growth	agr = %Δat	2008, JF	22.8% (1.58)	12.6% (0.78)
7	Basu	Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis.	Earnings to price	epx = ib/mve	1977, JF	–2.3% (–0.10)	–1.3% (–0.05)
8	Sloan, R.G.	Do stock prices fully reflect information in accruals and cash flows about future earnings?	Working capital accruals	acc = ((Δact-Δche)-(Δlct-Δdlc-Δtxp)-dp)/avgat	1996, TAR	7.7% (.104)	5.8% (0.47)
9	Hafzalla, Lundholm & Van Winkle	Repairing the accruals anomaly.	Percent accruals	pacc = (ib-oancf)/abs(ib); if ib=0 then scale by 0.01	2011, TAR	6.6% (1.24)	–0.3% (–0.03)

10	Houge & Loughran	Is cash flow king? Cognitive errors by investors.	Cash flow from operations	cflow = oancf/avgat	2000, JPFM	3.7% (0.26)	0.9% (0.09)
11	Chemmanur & Yan	Advertising, attention and stock returns.	Change in advertising exp	Δadv = ln(xad/xad_l1)	2009, WP	0.7% (0.04)	10.8% (0.51)
12	Chen & Zhang	A better three factor model that explains more anomalies	Capital expenditures and inventory	Δcapx = (Δppegt + Δinvt)/at_l1	2010, JF	20.0% (1.70)	8.6% (0.68)
13	Gu, Wang & Ye	Information in order backlog: Change vs. level.	Change in order backlog	Δob = ob/avgat	2008, WP	3.6% (0.38)	2.2% (0.13)
14	Prakash & Sinha	Deferred revenues and the matching of revenues and expenses.	Change in deferred revenues	Δdrev = Δdrc	Forthcoming, CAR	1.8% (0.09)	7.3% (0.41)
15	Pontiff & Woodgate	Shares outstanding and cross-sectional returns.	Change in shares outstanding	Δcsho = %Δcsho	2008, JF	13.5% (1.14)	8.7% (0.72)
16	Richardson, Sloan, Soliman & Tuna	Accrual reliability, earnings persistence and stock returns.	Change in long-term debt	Δlgr = %Δlt	2005, JAE	13.8% (1.63)	8.7% (0.71)
17	Richardson, Sloan, Soliman & Tuna	Accrual reliability, earnings persistence and stock returns.	Change in common shareholder equity	Δceq = %Δceq	2005, JAE	11.7% (0.99)	6.9% (0.56)
18	Soliman	The use of DuPont analysis by market participants.	Industry-adjusted change in profit margin	Δpmia, where pm = ib/sale, industry-adjusted	2008, TAR	-0.3% (-0.04)	2.0% (0.17)
19	Soliman	The use of DuPont analysis by market participants.	Industry-adjusted change in asset turnover	Δatoia, where ato = sale/avgat, industry-adjusted	2008, TAR	4.5% (0.90)	1.5% (0.14)
20	Thomas & Zhang	Tax expense momentum	Change in tax expense	Δtax = (txtq-txtq_l4)/at_l4	2010, WP	14.0% (1.71)	5.0% (0.41)
21	Rendelman, Jones & Latane	Empirical anomalies based on unexpected earnings and the importance of risk adjustments.	Unexpected quarterly earnings	sue = (aeps-feps)/price	1982, JFE	20.6% (2.34)	7.5% (0.38)
22	Brandt, Kishore, Santa-Clara & Venkatachalam	Earnings announcements are full of surprises.	3-day return around earnings announcement	ear	WP	13.2% (1.60)	3.5% (0.28)
23	Chandrashekar & Rao	The productivity of corporate cash holdings and the cross-section of	Cash to price	cash = (mve + dltt – at)/che	2009, WP	11.4% (1.00)	6.3% (0.49)

		expected stock returns.					
24	Hou & Robinson	Industry concentration and average stock returns.	Industry sales concentration	herf = industry sales concentration	2006, JF	5.0% (0.40)	0.1% (0.00)
25	Balakrishnan, Bartov & Faurel	Profit loss/profit announcement drift.	ROA	roaq = ibq/atq_l1	2010, JAE	11.6% (0.51)	6.6% (0.26)
26	Novy-Marx	The other side of value: good growth and the gross profitability premium.	Gross profitability	gma = (sale-cogs)/at_l1	WP	0.0% (0.00)	4.1% (0.24)
27	Lerman, Livnat & Mendenhall	The high volume return premium and post-earnings announcement drift.	Abnormal volume in earnings announcement month	aevol	WP	6.3% (0.90)	0.9% (0.07)
28	Chordia, Subrahmanyam, & Anshuman	Trading activity and expected stock returns	Dollar trading volume from month t-2	dvol = ln($tradingvolume) in month t-2	JFE, 2001	14.3% (0.79)	5.8% (0.34)
29	Bali, Cakici & Whitelaw	Maxing out: Stocks as lotteries and the cross-section of expected returns.	Maximum daily return in prior month	mxret	2011, JFE	-3.2% (-0.11)	14.4% (0.43)
30	Lamont & Frazzini	The earnings announcement premium and trading volume.	Earnings announcement month	emth = Long if earnings announcement month, short if not	WP	5.4% (0.93)	4.7% (0.76)
31	Diether, Malloy & Scherbina	Differences of opinion and the cross section of stock returns.	Dispersion in forecasted eps	disp = stdev(feps) /mean(abs(feps))	2002, JF	12.8% (0.81)	7.2% (0.32)
32	Hawkins, Chamberlin & Daniel	Earnings expectations and security prices.	Change in forecasted eps	Δfeps = mean(feps) – mean(feps_lag1mth)	1984, FAJ	14.4% (1.32)	6.7% (0.52)
32	Bauman & Dowen	Growth projections and common stock returns.	Forecasted growth in 5-year EPS	f5yrg = IBES forecasted long term growth rate in EPS	1988, FAJ	5.3% (0.19)	6.3% (0.22)

Notes: The Sharpe ratio for the market return is calculated after subtracting out the risk free rate from the numerator. However, we do not subtract out the risk free rate in calculating the Sharpe ratios of the 33 RPS because we assume that short-sale proceeds posted as collateral with the stock lenders—viz., the short rebate—earns the risk free rate.

TABLE 7

Cross-correlations of the monthly returns (1981-2010) of 33 readily programmed RPS. Each RPS is implemented in such a way that it generates a positive expected mean long/short hedge return. Pearson (Spearman) correlations are reported above (below) the diagonal.

Panel A: Cross-correlations between equally-weighted RPS returns

	market	mve	bm	m12m	m1m	Δm	agr	epx	acc	pacc	cflow	Δadv	Δcapx	Δob	Δdrev
market	1.00	0.26	-0.50	-0.43	0.39	0.24	0.03	-0.58	-0.29	-0.16	-0.43	-0.35	-0.15	-0.12	-0.07
mve	0.18	1.00	-0.07	-0.26	0.19	-0.06	0.64	-0.74	0.11	-0.20	-0.61	-0.81	0.47	-0.19	-0.31
bm	-0.48	0.06	1.00	0.23	-0.31	-0.20	0.31	0.45	0.38	0.21	0.48	0.34	0.40	0.00	-0.27
m12m	-0.33	-0.27	0.11	1.00	-0.67	-0.51	-0.03	0.53	0.13	0.04	0.32	0.30	0.17	0.23	0.04
m1m	0.41	0.19	-0.27	-0.51	1.00	0.65	-0.10	-0.37	-0.06	-0.09	-0.22	-0.26	-0.12	-0.11	0.14
Δm	0.25	-0.02	-0.17	-0.26	0.50	1.00	-0.21	-0.10	-0.01	0.13	0.09	-0.06	-0.16	-0.02	-0.03
agr	0.00	0.60	0.30	-0.17	0.10	-0.02	1.00	-0.47	0.38	-0.04	-0.39	-0.34	0.80	-0.28	-0.45
epx	-0.59	-0.63	0.37	0.50	-0.39	-0.15	-0.41	1.00	0.09	0.22	0.85	0.69	-0.20	0.27	0.19
acc	-0.34	0.15	0.42	0.05	-0.05	0.01	0.43	0.11	1.00	0.25	0.19	0.09	0.55	-0.04	-0.05
pacc	-0.17	-0.17	0.25	0.10	-0.16	0.05	0.01	0.19	0.28	1.00	0.46	0.25	-0.01	0.16	-0.07
cflow	-0.44	-0.53	0.40	0.37	-0.33	-0.03	-0.33	0.81	0.18	0.45	1.00	0.59	-0.12	0.27	0.09
Δadv	-0.28	-0.72	0.21	0.21	-0.18	-0.02	-0.29	0.59	0.11	0.23	0.49	1.00	-0.16	0.11	0.21
Δcapx	-0.12	0.45	0.37	0.03	-0.01	-0.04	0.77	-0.19	0.55	0.02	-0.14	-0.15	1.00	-0.20	-0.33
Δob	-0.08	-0.09	-0.01	0.14	-0.11	-0.05	-0.19	0.12	-0.07	0.13	0.14	0.02	-0.15	1.00	0.12
Δdrev	-0.27	-0.40	-0.13	0.20	-0.15	-0.11	-0.55	0.37	-0.02	-0.11	0.23	0.32	-0.39	0.11	1.00
Δcsho	-0.54	0.06	0.70	0.17	-0.22	-0.13	0.38	0.38	0.45	0.15	0.35	0.19	0.47	-0.02	-0.02
Δlgr	-0.13	0.48	0.34	0.04	-0.04	-0.14	0.72	-0.20	0.33	-0.03	-0.20	-0.22	0.69	-0.10	-0.41
Δceq	0.19	0.63	0.11	-0.32	0.22	0.03	0.82	-0.58	0.33	-0.02	-0.49	-0.35	0.60	-0.18	-0.49
Δpmia	-0.02	-0.02	0.00	-0.08	0.00	0.11	-0.11	0.02	-0.05	0.02	0.01	0.02	-0.08	0.06	-0.04
Δatoia	0.04	0.20	-0.04	0.08	0.03	0.07	0.10	-0.13	-0.08	0.00	-0.04	-0.18	0.06	0.06	-0.28
Δtax	0.18	-0.07	-0.24	0.36	-0.07	0.08	-0.19	0.04	-0.09	0.01	0.03	-0.06	-0.10	0.17	0.01
sue	-0.06	-0.04	-0.08	0.31	-0.09	-0.02	-0.04	0.10	-0.07	-0.09	0.06	-0.03	0.00	0.09	0.14
ear	-0.21	-0.06	0.15	0.41	-0.24	-0.27	-0.02	0.26	0.06	0.01	0.21	0.08	0.08	0.02	0.10
cash	-0.41	0.05	0.79	0.04	-0.12	-0.08	0.36	0.31	0.53	0.17	0.31	0.23	0.48	-0.11	-0.14
herf	-0.34	-0.32	0.09	0.19	-0.16	-0.13	-0.02	0.28	0.14	0.02	0.10	0.22	0.04	0.04	0.05
roaq	-0.48	-0.57	0.21	0.59	-0.37	-0.10	-0.41	0.79	0.00	0.14	0.68	0.48	-0.21	0.15	0.36
gma	-0.05	-0.32	-0.07	0.33	-0.16	0.02	-0.47	0.34	-0.30	0.02	0.34	0.23	-0.27	0.12	0.23
aevol	0.51	-0.02	-0.35	0.01	0.18	0.10	-0.07	-0.26	-0.28	-0.02	-0.17	-0.06	-0.09	0.03	0.06
dvol	-0.15	0.75	0.38	-0.41	0.08	-0.01	0.57	-0.34	0.28	-0.04	-0.25	-0.49	0.43	-0.15	-0.41
mxret	0.78	0.40	-0.47	-0.46	0.33	0.19	0.14	-0.78	-0.28	-0.13	-0.58	-0.45	-0.04	-0.12	-0.33
emth	0.35	0.02	-0.09	0.02	0.09	0.03	0.01	-0.13	-0.14	-0.10	-0.07	-0.01	0.00	0.02	-0.25
fedisp	-0.62	-0.29	0.26	0.51	-0.34	-0.14	-0.18	0.64	0.23	0.05	0.48	0.35	0.03	0.08	0.30
Δfeps	-0.18	-0.13	0.01	0.42	-0.18	-0.09	-0.14	0.18	0.07	0.06	0.12	0.06	-0.09	0.15	0.18
f5yrg	-0.64	-0.12	0.67	0.11	-0.31	-0.12	0.19	0.47	0.44	0.22	0.46	0.27	0.27	0.04	0.06

	Δcsho	Δlgr	Δceq	Δpmia	Δatoia	Δtax	sue	ear	cash	herf	roaq	gma	aevol	dvol	mxret	emth	fedisp	Δfeps	f5yrg
market	-0.53	-0.15	0.28	-0.07	0.01	0.06	-0.20	-0.34	-0.43	-0.35	-0.55	-0.15	0.52	-0.04	0.76	0.27	-0.68	-0.19	-0.64
mve	0.00	0.51	0.68	-0.07	0.20	-0.12	-0.14	-0.12	-0.01	-0.17	-0.65	-0.50	0.10	0.75	0.56	-0.10	-0.37	-0.15	-0.24
bm	0.76	0.38	0.03	0.08	0.02	-0.19	0.07	0.26	0.82	0.03	0.41	-0.01	-0.43	0.31	-0.53	-0.02	0.37	-0.01	0.77
m12m	0.42	0.15	-0.31	-0.21	0.11	0.47	0.53	0.66	0.14	0.29	0.61	0.22	-0.03	-0.44	-0.56	0.08	0.59	0.41	0.23
m1m	-0.39	-0.18	0.13	0.13	0.00	-0.24	-0.35	-0.48	-0.18	-0.27	-0.41	-0.04	0.12	0.19	0.37	-0.12	-0.36	-0.17	-0.32
Δm	-0.27	-0.24	-0.01	0.20	0.02	-0.10	-0.25	-0.51	-0.15	-0.31	-0.12	0.18	0.05	0.08	0.18	-0.12	-0.19	-0.12	-0.12
agr	0.46	0.77	0.83	-0.09	0.09	-0.13	0.02	0.03	0.36	0.04	-0.37	-0.56	-0.01	0.57	0.25	-0.02	-0.17	-0.16	0.18
epx	0.44	-0.23	-0.70	0.08	-0.03	0.12	0.27	0.40	0.33	0.10	0.89	0.54	-0.34	-0.42	-0.86	-0.01	0.69	0.21	0.58
acc	0.43	0.32	0.29	-0.01	-0.05	-0.02	0.03	0.16	0.52	0.10	0.10	-0.23	-0.27	0.26	-0.22	-0.12	0.25	0.00	0.39
pacc	0.09	-0.06	-0.06	0.02	0.00	0.01	-0.07	0.00	0.14	-0.06	0.20	0.11	-0.04	-0.04	-0.14	-0.05	0.04	0.05	0.22
cflow	0.40	-0.19	-0.57	0.10	0.03	0.05	0.08	0.25	0.37	-0.14	0.78	0.53	-0.28	-0.26	-0.69	0.01	0.51	0.07	0.58
Δadv	0.24	-0.23	-0.46	0.08	-0.18	0.03	0.13	0.19	0.30	0.10	0.63	0.41	-0.16	-0.56	-0.57	0.11	0.43	0.07	0.38
Δcapx	0.57	0.78	0.61	-0.11	0.09	-0.02	0.06	0.15	0.52	0.02	-0.12	-0.27	-0.05	0.42	0.02	-0.02	0.10	-0.11	0.27
Δob	0.00	-0.19	-0.29	0.03	0.15	0.20	0.06	0.15	-0.13	-0.03	0.27	0.19	0.00	-0.23	-0.23	0.07	0.17	0.16	0.07
Δdrev	-0.23	-0.39	-0.31	-0.02	-0.16	-0.03	0.18	0.08	-0.18	0.05	0.11	0.20	0.21	-0.36	-0.11	-0.09	0.04	0.09	-0.22
Δcsho	1.00	0.51	0.13	0.03	0.10	-0.11	0.17	0.37	0.67	0.07	0.43	-0.04	-0.37	0.26	-0.56	-0.08	0.46	-0.03	0.76
Δlgr	0.35	1.00	0.55	-0.14	0.09	-0.02	0.06	0.12	0.40	0.01	-0.14	-0.30	-0.09	0.47	0.03	-0.04	0.05	-0.05	0.25
Δceq	0.20	0.52	1.00	-0.08	0.02	-0.21	-0.14	-0.19	0.14	-0.04	-0.64	-0.59	0.12	0.56	0.53	-0.02	-0.43	-0.26	-0.10
Δpmia	-0.01	-0.11	-0.05	1.00	0.01	-0.15	0.00	-0.11	0.10	-0.08	0.08	0.03	-0.18	0.14	-0.10	-0.05	0.01	-0.09	0.16
Δatoia	0.00	0.07	0.08	0.04	1.00	0.06	0.00	0.05	-0.04	-0.14	-0.01	0.01	0.04	0.10	0.01	0.04	0.05	0.06	0.02
Δtax	-0.25	-0.09	-0.19	-0.07	0.06	1.00	0.48	0.39	-0.22	0.05	0.35	0.17	0.18	-0.33	-0.13	0.20	0.32	0.50	-0.20
sue	-0.05	0.06	-0.08	0.06	0.06	0.38	1.00	0.47	0.00	0.25	0.40	0.01	0.00	-0.19	-0.35	0.03	0.39	0.43	0.13
ear	0.18	0.11	-0.10	-0.07	-0.01	0.29	0.26	1.00	0.20	0.14	0.52	0.10	-0.09	-0.16	-0.48	0.10	0.49	0.31	0.28
cash	0.69	0.36	0.19	0.08	-0.05	-0.27	-0.09	0.11	1.00	0.15	0.25	-0.09	-0.38	0.29	-0.41	0.00	0.32	-0.09	0.65
herf	0.16	-0.02	-0.08	0.02	-0.16	-0.06	0.13	0.03	0.22	1.00	0.01	-0.29	-0.08	-0.23	-0.19	-0.05	0.18	0.21	0.10
roaq	0.21	-0.21	-0.59	0.01	-0.05	0.31	0.27	0.38	0.12	0.10	1.00	0.55	-0.26	-0.40	-0.86	-0.01	0.75	0.31	0.56
gma	-0.09	-0.27	-0.50	0.01	0.02	0.24	0.04	0.17	-0.16	-0.21	0.51	1.00	0.11	-0.45	-0.37	0.12	0.39	0.13	-0.03
aevol	-0.37	-0.14	0.01	-0.03	0.03	0.20	0.07	-0.03	-0.36	-0.16	-0.11	0.25	1.00	-0.32	0.46	0.24	-0.33	0.01	-0.56
dvol	0.34	0.47	0.54	0.06	0.11	-0.29	-0.10	-0.07	0.32	-0.21	-0.39	-0.40	-0.34	1.00	0.21	-0.25	-0.17	-0.20	0.25
mxret	-0.54	-0.04	0.34	-0.02	0.07	0.04	-0.16	-0.31	-0.42	-0.34	-0.67	-0.18	0.40	0.08	1.00	0.15	-0.79	-0.30	-0.69
emth	-0.17	0.01	0.00	0.00	0.03	0.21	0.03	0.07	-0.07	-0.09	-0.06	0.17	0.28	-0.17	0.26	1.00	-0.06	0.10	-0.20
fedisp	0.33	-0.03	-0.32	0.00	0.00	0.20	0.28	0.35	0.24	0.23	0.70	0.34	-0.28	-0.08	-0.71	-0.07	1.00	0.44	0.49
Δfeps	-0.03	-0.06	-0.19	-0.06	0.04	0.42	0.41	0.21	-0.04	0.21	0.31	0.09	0.00	-0.17	-0.23	0.12	0.42	1.00	0.00
f5yrg	0.71	0.20	0.04	0.06	-0.06	-0.29	-0.01	0.12	0.62	0.25	0.31	-0.20	-0.50	0.30	-0.60	-0.31	0.39	0.01	1.00

Panel B: Cross-correlations between value-weighted RPS returns

	market	mve	bm	m12m	m1m	Δm	agr	epx	acc	pacc	cflow	Δadv	Δcapx	Δob	Δdrev
market	1.00	-0.16	-0.04	-0.47	0.34	0.24	-0.35	-0.34	-0.05	-0.04	-0.18	-0.27	-0.21	-0.09	-0.05
mve	-0.21	1.00	0.20	-0.05	0.10	-0.06	0.14	-0.46	-0.14	0.09	-0.04	-0.56	0.06	-0.08	0.01
bm	-0.06	0.17	1.00	-0.10	-0.03	-0.16	0.45	-0.10	0.23	-0.10	0.00	0.07	0.33	0.02	-0.18
m12m	-0.35	-0.06	-0.08	1.00	-0.54	-0.34	0.23	0.51	-0.02	0.04	0.22	0.27	0.10	0.27	-0.05
m1m	0.32	0.09	-0.07	-0.46	1.00	0.47	-0.23	-0.32	-0.02	-0.08	-0.17	-0.26	-0.13	-0.11	0.37
Δm	0.14	-0.05	-0.15	-0.18	0.34	1.00	-0.24	-0.14	0.01	0.02	-0.09	-0.13	-0.05	-0.04	0.07
agr	-0.33	0.15	0.41	0.09	-0.12	-0.17	1.00	-0.03	0.23	-0.06	0.02	0.26	0.55	-0.05	-0.16
epx	-0.28	-0.43	-0.08	0.41	-0.30	-0.06	-0.05	1.00	0.08	-0.10	0.21	0.47	0.01	0.38	-0.08
acc	-0.13	-0.16	0.27	0.08	-0.15	-0.08	0.27	0.19	1.00	0.04	0.08	0.24	0.42	0.03	-0.15
pacc	-0.06	0.00	-0.09	0.07	-0.07	0.01	0.01	-0.05	0.06	1.00	0.57	-0.06	-0.01	0.03	-0.10
cflow	-0.19	-0.07	-0.06	0.22	-0.16	-0.09	-0.05	0.21	0.10	0.55	1.00	0.08	0.05	0.17	-0.18
Δadv	-0.24	-0.49	0.03	0.22	-0.26	-0.09	0.20	0.47	0.33	0.02	0.09	1.00	0.30	0.15	-0.05
Δcapx	-0.22	0.06	0.35	0.07	-0.12	-0.05	0.57	0.04	0.43	0.01	0.04	0.30	1.00	-0.01	-0.03
Δob	-0.03	-0.10	-0.01	0.13	-0.06	0.02	-0.04	0.20	0.03	0.01	0.15	0.13	-0.04	1.00	-0.12
Δdrev	-0.17	0.11	-0.21	0.07	0.05	0.02	-0.03	0.09	-0.02	-0.11	-0.06	0.08	0.10	0.13	1.00
Δcsho	-0.47	0.05	0.37	0.21	-0.19	-0.10	0.49	0.26	0.28	-0.10	0.01	0.33	0.41	0.11	0.10
Δlgr	-0.31	0.19	0.29	0.16	-0.13	-0.14	0.68	0.04	0.16	-0.05	-0.07	0.09	0.42	-0.05	-0.14
Δceq	-0.19	0.18	0.32	-0.04	-0.04	0.01	0.54	-0.22	0.28	0.04	-0.06	0.06	0.37	-0.11	-0.14
Δpmia	-0.14	0.08	0.01	0.01	-0.07	-0.05	0.05	0.01	-0.04	-0.04	-0.06	-0.07	0.06	0.00	0.01
Δatoia	-0.10	-0.02	-0.05	0.14	-0.02	0.03	0.02	0.11	-0.05	0.01	0.10	0.06	-0.01	0.17	0.13
Δtax	0.07	0.00	-0.22	0.28	-0.12	0.14	-0.11	0.07	-0.10	0.02	0.02	-0.02	-0.03	0.12	0.16
sue	-0.14	-0.05	-0.03	0.25	-0.23	-0.06	0.06	0.14	0.07	-0.05	0.06	0.04	0.02	-0.03	-0.15
ear	-0.10	0.06	-0.08	0.26	-0.16	-0.11	0.00	0.07	-0.08	0.01	0.03	0.03	-0.01	0.01	0.08
cash	-0.23	0.03	0.58	0.04	-0.16	-0.11	0.40	0.08	0.39	-0.12	-0.06	0.19	0.41	-0.02	-0.09
herf	-0.28	-0.06	0.02	0.15	-0.21	-0.06	0.15	0.29	0.14	0.00	0.09	0.06	0.06	0.00	0.08
roaq	-0.36	-0.33	-0.24	0.48	-0.32	-0.05	0.03	0.63	0.09	0.01	0.18	0.49	0.05	0.18	0.11
gma	-0.10	0.02	-0.47	0.16	-0.03	0.00	-0.20	-0.03	-0.38	0.09	0.11	0.02	-0.19	0.02	0.14
aevol	0.31	0.02	-0.18	-0.16	0.15	0.20	-0.10	-0.28	-0.13	0.03	-0.05	-0.11	-0.05	-0.04	0.01
dvol	-0.27	0.43	0.24	-0.03	-0.01	-0.11	0.24	-0.17	-0.03	0.08	0.06	-0.16	0.16	-0.01	0.07
mxret	-0.48	-0.26	-0.05	0.47	-0.27	-0.12	0.21	0.57	0.26	-0.02	0.16	0.56	0.21	0.14	0.01
emth	0.03	0.03	-0.19	0.03	0.07	0.01	-0.04	-0.05	-0.12	-0.02	0.05	-0.07	-0.03	-0.02	0.08
fedisp	-0.44	-0.19	-0.23	0.46	-0.25	-0.08	0.06	0.51	0.14	-0.01	0.17	0.42	0.08	0.16	0.14
Δfeps	-0.17	-0.05	-0.14	0.43	-0.14	-0.07	-0.05	0.24	0.09	0.04	0.08	0.17	0.00	0.12	0.16
f5yrg	-0.54	-0.07	0.34	0.24	-0.26	-0.19	0.42	0.46	0.42	-0.07	0.10	0.40	0.35	0.04	-0.06

	Δcsho	Δlgr	Δceq	Δpmia	Δatoia	Δtax	sue	ear	cash	herf	roaq	gma	aevol	dvol	mxret	emth	fedisp	Δfeps	f5yrg
market	-0.50	-0.41	-0.14	-0.20	-0.23	0.00	-0.22	-0.21	-0.17	-0.36	-0.42	-0.26	0.25	-0.16	-0.52	0.00	-0.53	-0.23	-0.54
mve	0.05	0.16	0.18	0.14	0.02	-0.05	-0.13	0.05	-0.04	-0.06	-0.37	0.02	0.00	0.42	-0.33	0.03	-0.23	-0.04	-0.14
bm	0.47	0.34	0.31	0.05	-0.05	-0.18	-0.08	-0.11	0.65	0.00	-0.14	-0.50	-0.28	0.29	-0.09	-0.14	-0.19	-0.18	0.36
m12m	0.39	0.35	-0.13	0.04	0.23	0.36	0.41	0.41	0.02	0.19	0.59	0.35	-0.10	-0.11	0.61	0.11	0.57	0.44	0.34
m1m	-0.27	-0.29	0.00	-0.08	-0.04	-0.21	-0.34	-0.19	-0.14	-0.20	-0.38	-0.15	0.12	0.00	-0.35	-0.02	-0.29	-0.20	-0.27
Δm	-0.24	-0.31	0.07	-0.10	-0.05	0.08	-0.12	-0.21	-0.14	-0.14	-0.14	-0.06	0.22	-0.09	-0.21	-0.06	-0.14	-0.05	-0.20
agr	0.62	0.78	0.47	0.11	0.03	0.02	0.21	0.10	0.45	0.25	0.21	-0.12	-0.19	0.22	0.25	0.02	0.14	0.01	0.52
epx	0.37	0.15	-0.33	0.05	0.19	0.13	0.13	0.17	0.10	0.19	0.70	0.09	-0.25	-0.21	0.67	0.00	0.60	0.25	0.52
acc	0.18	0.15	0.27	-0.04	-0.09	-0.05	-0.05	-0.14	0.42	0.12	0.08	-0.40	-0.09	-0.03	0.11	-0.09	0.07	0.01	0.35
pacc	-0.17	-0.14	0.07	-0.06	0.00	0.06	-0.08	-0.08	-0.20	-0.01	-0.05	0.05	0.07	0.05	-0.14	-0.06	-0.03	0.11	-0.11
cflow	0.03	0.00	-0.04	-0.10	0.11	0.05	0.15	-0.01	-0.02	0.10	0.16	0.10	-0.01	0.00	0.17	0.01	0.19	0.12	0.15
Δadv	0.40	0.22	-0.01	-0.10	0.08	0.06	0.15	0.10	0.26	0.10	0.56	0.06	-0.14	-0.17	0.56	-0.07	0.48	0.19	0.49
Δcapx	0.43	0.44	0.39	0.10	-0.05	0.02	0.01	0.04	0.42	0.08	0.13	-0.12	-0.05	0.15	0.19	-0.03	0.13	0.01	0.37
Δob	0.21	0.03	-0.20	0.05	0.24	0.16	-0.07	0.04	0.02	-0.08	0.30	0.01	-0.05	-0.08	0.25	0.00	0.29	0.19	0.18
Δdrev	-0.20	-0.25	-0.08	0.11	0.14	-0.09	-0.08	0.11	-0.20	0.01	-0.09	0.22	0.14	0.06	-0.06	-0.05	-0.02	-0.11	-0.22
Δcsho	1.00	0.62	0.26	0.20	0.14	0.02	0.13	0.17	0.51	0.21	0.44	-0.10	-0.30	0.13	0.50	0.05	0.43	0.09	0.68
Δlgr	0.36	1.00	0.26	0.14	0.12	0.03	0.23	0.15	0.38	0.16	0.30	-0.05	-0.25	0.16	0.36	0.01	0.26	0.07	0.50
Δceq	0.34	0.32	1.00	0.11	-0.03	-0.09	0.04	-0.11	0.29	0.11	-0.25	-0.14	0.02	0.19	-0.12	-0.08	-0.11	-0.08	0.13
Δpmia	0.16	0.06	0.05	1.00	0.02	-0.02	-0.08	-0.01	0.05	0.04	0.02	0.09	-0.06	0.11	0.03	0.00	0.05	-0.10	0.07
Δatoia	0.09	0.06	0.02	-0.03	1.00	0.09	-0.04	0.24	0.02	-0.03	0.20	0.14	-0.08	-0.08	0.17	0.06	0.22	0.07	0.12
Δtax	-0.13	-0.05	-0.09	-0.04	0.09	1.00	0.28	0.21	-0.04	-0.07	0.37	0.15	0.17	-0.11	0.10	0.12	0.24	0.29	-0.03
sue	0.03	0.16	0.01	-0.02	-0.02	0.25	1.00	0.16	0.12	0.35	0.29	0.16	0.02	-0.02	0.35	-0.01	0.25	0.30	0.18
ear	0.02	-0.01	-0.05	-0.06	0.14	0.23	0.02	1.00	-0.03	0.10	0.25	0.28	-0.02	-0.05	0.25	0.05	0.27	0.19	0.09
cash	0.39	0.30	0.27	0.05	0.04	-0.08	0.18	0.00	1.00	0.19	0.11	-0.47	-0.28	0.19	0.13	-0.02	0.02	-0.11	0.51
herf	0.19	0.06	0.04	0.00	-0.04	-0.08	0.23	0.06	0.30	1.00	0.12	-0.01	-0.13	0.00	0.25	0.03	0.26	0.15	0.39
roaq	0.22	0.07	-0.16	0.01	0.18	0.26	0.21	0.20	0.00	0.17	1.00	0.22	-0.23	-0.17	0.70	0.07	0.67	0.35	0.56
gma	-0.15	-0.16	-0.13	0.06	0.06	0.14	-0.08	0.14	-0.49	-0.18	0.22	1.00	0.15	-0.18	0.23	0.21	0.33	0.22	-0.19
aevol	-0.23	-0.13	0.01	-0.07	-0.10	0.15	-0.05	-0.11	-0.22	-0.20	-0.26	0.15	1.00	-0.21	-0.20	0.07	-0.06	-0.07	-0.33
dvol	0.13	0.21	0.16	0.11	-0.02	-0.08	0.03	-0.03	0.16	0.01	-0.14	-0.09	-0.14	1.00	-0.18	-0.17	-0.24	-0.11	0.06
mxret	0.40	0.21	0.06	0.02	0.07	0.02	0.21	0.12	0.18	0.23	0.61	0.08	-0.25	-0.08	1.00	0.05	0.69	0.27	0.62
emth	-0.04	-0.10	-0.10	0.00	0.06	0.09	-0.09	0.03	-0.13	0.02	0.02	0.22	0.11	-0.14	0.00	1.00	0.09	0.06	-0.05
fedisp	0.28	0.09	-0.02	-0.01	0.11	0.16	0.14	0.11	0.01	0.26	0.62	0.29	-0.12	-0.18	0.60	0.11	1.00	0.45	0.47
Δfeps	0.03	-0.03	-0.05	-0.14	0.05	0.22	0.22	0.16	-0.07	0.13	0.32	0.14	-0.10	-0.07	0.27	0.10	0.40	1.00	0.15
f5yrg	0.57	0.33	0.25	0.09	0.09	-0.16	0.13	-0.02	0.50	0.37	0.35	-0.24	-0.36	0.13	0.54	-0.09	0.35	0.10	1.00

TABLE 8

Average cross-correlations and average absolute cross-correlations between the monthly returns (1981-2010) of 33 readily programmed RPS from our database of the population of RPS discovered and publicly reported during 1970-2010. Each RPS is implemented in such a way that it generates a positive expected mean long/short hedge return.

Panel A: Average cross-correlations between monthly RPS returns

	1981-1990	1991-2000	2000-2010	1981-2000
Using all 33 signals:				
Average EW-RPS cross-correlation	0.04	0.01	0.05	0.03
Average VW-RPS cross-correlation	0.05	0.03	0.07	0.05
Using only signals with abs(t-stat) > 1.96:				
Average EW-RPS cross-correlation	0.06	0.02	0.07	0.06
Average VW-RPS cross-correlation	0.07	0.03	0.10	0.07

Panel B: Average absolute cross-correlations between monthly RPS returns

	1981-1990	1991-2000	2000-2010	1981-2000
Using all 33 signals:				
Average absolute value of EW-RPS cross-correlations	0.25	0.28	0.27	0.24
Average absolute value of VW-RPS cross-correlations	0.19	0.18	0.22	0.18
Using only signals with abs(t-stat) > 1.96:				
Average absolute value of EW-RPS cross-correlations	0.24	0.25	0.27	0.23
Average absolute value of VW-RPS cross-correlations	0.23	0.20	0.26	0.21