The Remarkable Multidimensionality in the Cross-Section of Expected U.S. Stock Returns

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Abstract

20+ years after Fama & French (1992), we re-measure the dimensionality of the cross-section of expected U.S. monthly stock returns in light of the large number of return predictive signals (RPS) that have been identified by business academics over the past 40 years. Using 100 readily programmed RPS, we find that a remarkable 24 are multidimensionally priced as defined by their mean coefficients having an absolute t-statistic ≥ 3.0 in Fama-MacBeth regressions where all RPS are simultaneously projected onto 1-month ahead returns during 1980-2012. We confirm the high degree of dimensionality in returns using factor analysis of RPS, factor analysis of long/short RPS hedge returns, LASSO regression, regressions of portfolio returns on RPS factor returns, and out-of-sample RPS hedge portfolio returns. We put forward a new empirically determined 10-RPS model of expected returns for consideration by researchers and practitioners. We also discuss other implications of our findings, chief of which is the need for research that explains why stock returns are so multidimensional and why the most empirically important RPS are priced the way they are.

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1. Introduction

In their seminal study, Fama and French (1992, FF92) measured the dimensionality of the cross-section of expected monthly U.S. stock returns. After jointly evaluating the roles of beta, firm size, book-to-market, earnings-to-price and leverage, they observed that while beta was not associated with expected returns, firm size and book-to-market were, and in a manner that absorbed the unidimensional explanatory power of earnings-to-price and leverage. FF92 concluded that over the period 1963-1990, the cross-section of monthly U.S. stock returns was two-dimensional, but that neither dimension was consistent with the CAPM. A third dimension in the form of 12-month return momentum (Jegadeesh, 1990; Jegadeesh and Titman, 1993) was added in Fama and French (1996) and Carhart (1997) to create what has for two decades been seen in academia and much investment practice as the default and conventional three-dimensional set of firm-specific risks that explain equity returns (Royal Swedish Academy of Sciences, 2013, p.43).

The chief goal of our paper is to re-measure the dimensionality of the cross-section of expected U.S. stock returns in light of the 330+ firm-level return predictive signals (RPS) that have been identified by business academics since 1970 (Green, Hand and Zhang, 2013; Harvey, Liu and Zhu, 2013). By updating the empirical dimensionality of the cross-section of expected monthly returns, our study carries out Cochrane's 2010 AFA Presidential Address in which he issues a 'multidimensional challenge' and calls for Fama and French's 'anomaly digestion exercise' to be repeated, and executes Goyal's (2012) recent call for researchers to 'synthesize the huge amount of collected [RPS] evidence.' In doing so, we seek to answer two of the main questions posed by Cochrane namely: "Which characteristics really provide independent information about mean returns?" and "Which characteristics are subsumed by other RPS?" (Cochrane 2011, p.1060),

Our main finding is that over the period 1980-2012, the dimensionality of monthly U.S. stock returns is almost 10 times that originally estimated by FF92. Specifically, we document that 24 out of 100 previously documented RPS are reliably multidimensionally priced, as defined by their mean coefficient estimate having an absolute t-statistic ≥ 3.0 in Fama-MacBeth regressions where all 100 RPS are simultaneously projected onto 1-month ahead returns.[1,2] The remarkable degree of

[1] While we use the present tense when describing the dimensionality of returns, we recognize that our analysis is historical and so may not describe the dimensionality of returns going forward beyond our sample period.

[2] We use 3.0 as the absolute t-statistic cutoff for inferring statistical significance based on the insights of Harvey, Liu, and Zhu (HLZ, 2013). HLZ seek to answer the related but different question of whether the documented hedge returns to unidimensioned RPS are real or whether they are statistical artifacts stemming from multiple testing of the

multidimensionality we observe in part reflects the fact that the mean absolute cross-correlation among RPS as measured in scaled decile ranks is small, just 0.08. We confirm the high degree of dimensionality in several ways, including through factor analysis of RPS, factor analysis of long/short RPS hedge returns, LASSO regression, out-of-sample RPS hedge portfolio returns, and regressions of portfolio returns on RPS factor-mimicking-portfolio returns.

A second goal of our study is to describe key economic aspects of RPS pricing when viewed from a multidimensional perspective. Among a number of results, we observe that although firm size, book-to-market, and 12-month momentum in certain instances provide a reasonable representation of expected returns, the restricted three-dimensional model misses economically important aspects of the cross-section of returns. For example, we show that only infrequently do firm size, book-to-market, and 12-month momentum have multidimensioned t-statistics that are large enough to place in the top ten t-statistics of all multidimensioned RPS, and when used alone as a set of characteristics, firm size, book-to-market, and 12-month momentum miss a large portion of the variation that is explained by the expanded set of 24 multidimensionally priced RPS. We also observe that while large-cap firms have far fewer multidimensionally priced RPS than do mid-cap or small-cap firms, their RPS explain three times as much cross-sectional variation in returns, and that the hedge returns earned by multidimensioned RPS are on average one half to two thirds smaller than those earned by unidimensioned RPS and their t-statistics are 50% smaller. Additionally, and of potential importance to practitioners, we document that the out-of-sample standard 2X gross levered hedge portfolio of the full set of RPS that we study yields a monthly return of 2.7% with an annualized Sharpe ratio of 2.6. We unpack these findings in more detail in sections 4-6.

The last objective of our paper is to present some of the implications we believe our study has for past and future research that focuses on, or uses, monthly U.S. stock returns. In this regard, first and foremost we propose that prior research has focused on too few RPS, and on RPS that are distant from what empirically are the most important RPS. Not only are there almost ten times more RPS that matter in the cross-section of future monthly stock returns than firm size, book-to-market and 12 month momentum, and not only does the full set of multidimensioned RPS explain between three and nine times the cross-sectional variation as firm size, book to market and 12 month momentum, but the most important RPS as judged by their multidimensioned t-statistics are not firm size, book-to-market and 12 month momentum. Rather, the RPS that matter most are somewhat

same underlying data. After rigorous statistical analysis, they conclude that an absolute t-statistic of 3.0 offers sufficient protection against data-snooping.

underappreciated firm characteristics such as the three-day return centered on the most recent earnings announcement, quarterly sales growth, trailing and forecasted annual earnings-to-price ratios, and 12 month industry return momentum. This leads us to suggest that there is likely to be substantial value to future research seeking to understand why stock returns are so highly dimensional, why the most empirically important RPS are priced the way they are, and what kinds of market efficiency or pricing equilibria are consistent with such a high degree of return multidimensionality. We therefore see there being much less benefit to discovering new RPS before insight is gained into the large number of RPS that have already been discovered.

We also suggest that the multidimensionality we document draws attention to the increasing gap between academic finance research and actual investment practice. Although a small number of RPS have dominated the academic literature as benchmarks for expected returns, the use of multidimensional models of returns has become common among large and quantitatively oriented equity investment practitioners. In this regard, based on our findings we propose a new empirically determined 10-RPS model to describe the cross-section of expected U.S. monthly returns that researchers and practitioners may find value in using. We also argue that our results highlight a need for greater connectedness between academics and practitioners, and the value of research focused on the empirical regularities relied on by the best investment professionals. To the best of our knowledge, practitioners only infrequently have strong theoretical foundations for why they include a multitude of RPS in their return prediction and risk management models, relying instead on the practical objective of using models that work in real-world equity investing.

Another implication of our study is the material likelihood that a sizeable number of past papers that have inferred that a newly discovered RPS is statistically and/or economically significant may have been mistaken, at least with regard to the generalizability of that inference to the overall 1980-2012 period we analyze. Using the data-snooping-adjusted t-statistic of 3.0 proposed by Harvey, Liu and Zhu (2013), even though RPS are only weakly cross-correlated, we find that 75% of the large set of RPS we study are <u>not</u> multidimensionally priced.[3] Adding to this, our finding that the hedge returns earned by multidimensioned RPS are on average one half to two thirds smaller than those earned by unidimensioned RPS implies that the economic importance of any given RPS—when

[3] We also only find statistical significance in the unidimensional regressions for approximately half of the 100 RPS that we study, most likely driven by the sensitivity of RPS significance to modifications to measurement and sample changes and to our choices used to align all RPS in calendar time for all firms.

appropriately measured at the margin after controlling for the economic importance of other RPS—is likely somewhat smaller than previously thought.

The concluding implication we argue for is that the true dimensionality in returns is likely far larger than we have estimated. Although we have analyzed the largest number of RPS yet in the academic literature, the 100 RPS we study are not highly cross-correlated and represent less than one third of the 330+ RPS that have been publicly identified by business academics (Green, Hand and Zhang, 2013; Harvey, Liu and Zhu, 2013). Moreover, the replicable but necessarily unrefined choices we make to combine RPS across companies and time periods and databases, our using only those RPS that can be calculated from CRSP and Compustat and I/B/E/S, our approach to dealing with missing data, and our measuring the average of pre- and post-publication coefficients all likely serve to hinder not help us measure RPS to the same accuracy as in the originating RPS papers and therefore the form of the signals actually reacted to and priced by investors.

The remainder of our paper proceeds as follows. In section 2 we review the prior literature on dimensioning expected returns. In section 3 we describe the sample of RPS we employ and the choices we make during the process of selecting, aligning and coding them. In sections 4 and 5 we report our main findings regarding the multidimensionality in returns, and the results of a battery of tests aimed at validating the presence of high dimensionality. In section 6 we present the results of comparing and contrasting key economic aspects of multidimensionally versus unidimensionally priced RPS. We highlight the main limitations of our study in section 7, and conclude in section 8.

2. Prior Literature on Dimensioning the Cross-Section of Expected Stock Returns

Since Fama and French (1992), Jegadeesh and Titman (1993), and Fama and French (1996) together set in place the widespread view that firm size, book-to-market and 12-month momentum dimension the cross-section of expected U.S stock returns, relatively few papers have directly empirically revisited the dimensionality of returns. This contrasts with the steady development of a vast literature that has identified hundreds of firm-specific RPS that predict the cross-section of future stock returns in the sense that any given RPS is incrementally priced beyond one or more of the default and conventional three-dimensional set of firm-specific risks that explain equity returns—namely, firm size, book-to-market and 12-month momentum. For example, Subrahmanyam (2010) identifies 50 RPS, McLean and Pontiff (2013) identify 82 RPS, Harvey, Liu and Zhu (2013) identify 311 RPS and/or factors, and Green, Hand and Zhang (2013) identify 330 RPS.

Papers that have studied the dimensionality of returns have either proposed a small competing set of priced RPS to replace firm size, book-to-market and 12-month momentum, or have put forward only a modestly larger set of priced RPS beyond firm size, book-to-market and 12-month momentum. Hou, Xue and Zhang (2012), Light, Maslov and Rytchkov (2013) and Fama and French (2013) exemplify the former approach, while Jacobs and Levy (1988), Haugen and Baker (1996), Fama and French (2008) and Lewellen (2013) illustrate the latter method.

Motivated by *q*-theory, Hou, Xue and Zhang (2012) argue that a model consisting of the excess market return, a small-minus-big firm size factor, a high-minus-low investment factor and a high-minus-low return on equity factor performs similarly to firm size, book-to-market and 12-month momentum but also captures many patterns that are anomalous to firm size, book-to-market and 12-month momentum. As such, Hou, Xue and Zhang propose that their four factor model is "a new incarnation of Fama and French (1996)" (p.4) in that it is an alternative factor-based model for estimating the cross-section of expected stock returns. Indeed, Hou, Xue and Zhang even go as far as to propose that any new anomaly variable should be benchmarked against their q-factor model to see if the variable provides any incremental information (p.35). In a related approach, Fama and French (2013) develop a five-factor model that augments the three-factor model of Fama and French (1993) by adding profitability (Novy-Max, 2012) and investment (Aharoni, Grundy and Zeng, 2013) factors. Treating expected returns as latent variables, Light, Maslov and Rytchkov (2013) take a different tack by developing a procedure that uses 13 RPS, from which they construct two new RPS, one of which they argue combines information from all anomalies.

Opposite to Hou, Xue and Zhang's focus on a small-in-number competitor set of RPS, Jacobs and Levy (1988), Haugen and Baker (1996) and Lewellen (2013) directly examine whether a larger set of RPS than firm size, book-to-market and 12-month momentum are multidimensionally priced. Thus Jacobs and Levy (1988) comprehensively analyze 25 RPS known to academics at the time and find that 10 are reliably multidimensionally priced. Haugen and Baker report that out of 40 interrelated RPS they choose in an ad hoc manner that is only partially based on prior published research, a total of 11 RPS are reliably multidimensionally priced, while Fama and French (2008) and Lewellen (2013) show that from a more rigorously prescribed set of RPS taken from prior academic research, six out of seven RPS, and nine out 15 RPS, respectively, are reliably multidimensionally priced using the Harvey, Liu and Zhu (2013) absolute t-statistic ≥ 3.0 cutoff that we adopt in our paper.[4] In the practitioner sphere, large and sophisticated quantitative investors such as Axioma, BGI/BlackRock, Jacobs-Levy Equity Management, MSCI/Barra, Northfield, and JP Morgan (to name but a few) have for many years successfully developed and used equity models that contain far more factors than firm size, book-to-market and momentum.

These studies notwithstanding, the thesis of our paper is that prior research has not yet executed on the multidimensional challenges issued by Cochrane (2011) and Goyal (2012). Prior empirical research has studied but a small fraction of the 330+ RPS identified by academics. It is the existence of such a "veritable zoo" of RPS—particularly those that have not been highly cited yet in their originating papers exhibit mean hedge returns and Sharpe ratios that are far larger than those of highly cited RPS—that leads us to propose that FF92's original and very useful data reduction warrants repeating and the results placed into the public domain. Executing this re-measurement is the focus of our paper.

3. Data and Methodology

3.1 RPS dataset of integrated CRSP, Compustat and I/B/E/S data aligned in calendar time

Because the goal of our paper is to simultaneously project a large number of RPS onto 1-month-ahead returns, we face decisions about how many RPS to include, how to combine RPS across companies, time periods and databases, and how to address missing data. To maximize the ability of researchers to replicate and/or expand from our work, we seek to transparently detail the choices we made in selecting, aligning and coding our RPS. Some choices unavoidably distance us from either the exact research design used in the original papers, or the exact definitions of RPS, or the exact sample periods used in the originating papers. However, we expect this will make it less likely that we will observe multidimensional statistical significance for some RPS, and thus make it more likely that we will underestimate the true degree of multidimensionality in U.S. stock returns.

We emphasize another critical aspect regarding our data and methodology choices. One of the persistent concerns in research studying predictability in stock returns has been the ways in which data snooping can enter into individual studies and research that collectively analyzes the same data. We therefore carefully define the standardized data coding approaches that we uniformly apply to all

[4] Many of the 40 RPS used by Haugen and Baker (1996) are highly correlated variants of few constructs, with the likely result that the analysis in Haugen and Baker is based on fewer than 40 independent RPS. Fama and French (2008) orient their analysis around the question of whether RPS pricing is robust across firm size. Lewellen (2013) focuses his study on the cross-sectional dispersion and out-of-sample predictive ability of the stock return forecasts that he extracts from the particular set of 15 RPS that he employs.

companies and all RPS in our study with the goal of seeking to avoid further contaminating our research through creating the additional concern of data snooping. Once again, we expect this choice to make it likely that we underestimate, not overestimate, the multidimensionality of returns.

The most complete way to measure the degree of dimensionality in expected stock returns would be to use the entire population of known RPS. We judged this to be infeasible given Green, Hand and Zhang (2013) and Harvey, Liu and Zhu (2013) each catalogue over 310 different RPS and/or factors across many different data sources in their approximations of the population of RPS publicly identified by business faculty. In Figure 1, we highlight the cumulative number of RPS that have been publicly documented by business academics between 1970-2010 by aggregating across the accounting-based, finance-based and other-based categories RPS reported in Figure 1 of Green, Hand and Zhang (2013).

To balance the benefits of analyzing the largest number of RPS with the costs of gathering, programming and analyzing the relevant data, and also seeking to not erect barriers to the replicability of our work, we selected 100 RPS primarily from the Green, Hand and Zhang database, requiring only that each RPS be based entirely on CRSP, Compustat and I/B/E/S data items.[5] Our dataset spans the period Jan. 1980 - Dec. 2012. We begin in 1980 because 1980 represents a point at which most of the RPS data items are robustly available. We end in 2012 because 2012 was the date of the most recently available data as of the writing of the initial draft of our paper.

The full set of our 100 RPS are reported in Table 1, listed in the order in which the RPS were first published, or where not yet published, appeared as a working paper. We also provide the acronyms we use, and the authors, journal and year of publication or working paper status. Inspection of Table 1 shows that the RPS we select span both highly and sparsely cited papers, published and working papers, and publication dates that spread out between 1977 and 2013. On some occasions we identify several RPS from one paper.

Table 2 defines from a programming point of view each RPS implemented in our study, where for purposes of easy reference vis-à-vis the Tables we present later in our paper, the RPS listed in Table 1 are sorted alphabetically by acronym. Monthly stock returns are collected for the month following that at which the RPS data is available. Missing Compustat and I/B/E/S data are the main reason that very few RPS can be computed for every firm at every point in calendar time. However, deleting observations with missing Compustat and I/B/E/S data would greatly reduce both the

[5] We also restricted the RPS to main effect signals. We do not include RPS that are interactions between other RPS.

number of observations and/or firms included in our analysis and the representativeness of our results. To avoid this, Table 3 details our data retention strategy, relative to our baseline of starting with all firms with common stock traded on the NYSE, AMEX or NASDAQ exchanges. We proceed as follows.

Following FF92 we exclude approximately 46 observations per month where market cap and/or book value of equity were unavailable (panel A). Second, we deleted a few observations due them having implausibly extreme or impossible monthly returns (panel B).[6] We then reset 19 Compustat missing data items such as R&D expense, intangible assets and total inventory to zero if they are reported missing by Compustat (panel C).[7] This approach follows prior research and for the largest set of missing values makes some sense. For example, R&D expense is often reported as missing for companies with no R&D expense or with R&D expense that is small enough that the firm aggregates it with another financial statement line item.[8] We also set one I/B/E/S data item with missing values to zero, namely analyst following *nanalyst*. I/B/E/S is the most restrictive of our databases in terms of its coverage of companies and the sample time period available, so we only use I/B/E/S-based RPS starting in January 1989 when more expansive coverage begins.[9] We note that while setting a large number of missing observations across several data items to zero preserves the large number of RPS values, it also likely reduces the quality of the RPS in that it injects into their measurement largely uninformative zero values. This too will make it more likely that our statistical analysis will underestimate the dimensionality of returns.

We then integrated the missing-value-adjusted data across Compustat, I/B/E/S and CRSP databases, and proceed to compute and align RPS in calendar time. Since Green, Hand and Zhang (2013) report that 57% of the 330 RPS in their database study the RPS through the lens of monthly returns, we re-measure and align RPS each month.[10] While monthly updating is consistent with the

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[6] We include delisting returns following Shumway and Warther (1999).

[7] In doing so, we follow what is commonly done by quantitative practitioners. For balance sheet variables that are missing in the quarterly Compustat database at the quarterly frequency but are available on an annual basis, we set the quarterly values to the most recent annual values.

[8] One notable exception though is the number of employees, in that a company with an unreported number of employees is unlikely to be a company with zero employees.

[9] With the number in parenthesis being that shown in Tables 1 and 2, the RPS that use I/B/E/S are *sue* (#6), *chfeps* (7), *fgr5yr* (#9), *sfe* (#49), *nanalyst* (#50), *disp* (#51) and *chnanalyst* (#75).

[10] In aligning RPS in calendar month time we use the following conventions. At the end of each calendar month, the most recent annual financial statement information is assumed to be available if the fiscal year ended at least 5 months prior to the month end. Quarterly financial statement information collected from Compustat is assumed to be available with at least a 60-day lag, and I/B/E/S and CRSP information are aligned in calendar time using the I/B/E/S statistical period date and the CRSP monthly or daily end date. We obtain similar results assuming a 90-day

portfolio rebalancing approach used by many quantitative institutional investors, practitioners may update the data aspects of their RPS as often as every minute or as infrequently as every 12 months. We expect monthly updating to adequately tradeoff the lower transactions and trading costs at longer frequencies with the greater timeliness from RPS that are updated at shorter frequencies. Necessarily, though, our monthly RPS construction means that the RPS in our dataset that come from studies that employ a shorter-than-monthly frequency will use signals that are less timely than in prior studies, while those RPS that come from studies using longer frequencies will use more timely information. This slippage further degrades our ability to detect multidimensionally priced RPS.

Finally, once calculated using the data at the end of the steps just described, we reset all missing values of RPS to the winsorized mean of the non-missing RPS values for that calendar month.[11] We do so to retain as many firm-month RPS observations as possible. In panel D we report the number of firm-month observations in our full dataset of 1,987,340 firm-month observations spanning Jan. 1980 - Dec. 2012 before setting missing RPS values to each RPS' monthly mean, and the associated percentage of firm-month observations in which we then set missing RPS values to each RPS' monthly mean. The mean percentage of firm-month observations where we reset missing RPS values to each RPS' monthly mean value is 10%.[12]

3.2 Construction and limitations of scaled decile ranked RPS

We seek to mitigate the inferential error risks that can arise from data-error outliers by using monthly cross-sectional scaled decile rankings of each continuous or non-indicator RPS in our return prediction regressions. We implement the scaled decile ranked approach at the end of every calendar month by ranking each non-indicator RPS into deciles where zero is the lowest decile and nine is the highest decile, and then dividing the decile number by nine. The resulting scaled decile ranked RPS are created after resetting missing RPS values to each RPS' monthly mean. We perform this scaling approach separately for each sample. Thus, for the sample of all firms the ranking is done across all

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lag. Our adopting a 60 day lag is intended to balance making sure financial statement data is available to the stock market, and preventing certain earnings announcement related RPS from getting too stale.

[11] The winsorized mean is the mean calculated after extremes that are more than 3X the interquartile range (IQR) below the first quartile Q1 or above the third quartile Q3 are reset to Q1 – [3 x IQR] or Q3 + [3 x IQR], respectively, for continuous RPS with positive and negative values. RPS with only positive values are winsorized only at the largest positive side of the distribution. Results are very similar when winsorizing at both tails of the distribution. In unreported findings, our inferences about the general scale of multidimensionality in stock market returns, as well as the inferences regarding most RPS, are unchanged if we use non-scaled decile ranked RPS or winsorized RPS.

[12] We recognize that there are more sophisticated methods that could be used to infill missing observations (e.g., modeling missing observations as a function of firm characteristics). We adopt a simple approach in order to increase the replicability of our findings and decrease the likelihood of creating data snooping biases.

firms each month; similarly for large-cap, mid-cap, and small-cap firms the ranking is done separately by market cap grouping each month.

The scaled decile ranking approach directly follows work by Fama (1976, Ch.9, pp.326-329). In addition to minimizing the effects of outliers on our regression parameter estimates, the method yields coefficient estimates that have a ready and powerful economic interpretation that is lacking in other approaches to measuring RPS. Specifically, Fama shows that the coefficients estimated from cross-sectional regressions of returns onto RPS that are scaled to lie $\in [0,1]$ are the returns to linearly optimal (pre-transactions costs) dollar-neutral in-sample RPS hedge portfolios that are orthogonal to all other RPS included in the regressions.[13]

3.3 *Measuring and adjusting for high collinearity amongst a small subset of RPS*

Last in terms of constructing our RPS dataset, we measure the degree of cross-correlation among our 100 RPS and seek to address the high collinearity that we find exists within a small minority of signals. We do so because while high collinearity among independent variables in OLS regressions does not create bias in the resulting estimated slope coefficients, it does increase their standard errors, sometimes very substantially. To the extent that we are able to identify particular RPS that have large cross-correlations with other RPS because they are definitionally or economically very closely related to each other—for example, beta and beta squared—we choose in our study to include fewer RPS in our analysis in exchange for more precise standard errors on the RPS that are included.

Panel A of Table 4 reports the distribution of the variance inflation factors (VIFs) from an initial pooled time-series cross-sectional regression of 1-month-ahead returns onto all 100 RPS.[14] While the median VIF of 2.1 is not large, 15 VIFs exceed 6.0. We therefore reduce the number of RPS to where the maximum VIF is below 6.0. In doing so, we find that after removing the nine RPS listed on the right hand side of panel A, the VIFs of the remaining 91 RPS in a new pooled time-series cross-sectional regression of 1-month ahead stock returns onto the 91 RPS are 5.2 or less.

[13] Technically, the zero investment portfolio interpretation relies on the regression including an intercept, which is always the case in our analyses. Inclusion of an intercept ensures that the weighted average of the focal RPS, measured in scaled decile ranks, is one, and that the weighted averages of the other RPS included in the regression are zero. The return on the zero-investment portfolio is of course only optimal if the assumption that the RPS is linearly related to the scaled decile ranks is correct. Abarbanell and Bushee (1998) is one of the few studies that has used one or more RPS measured in scaled decile ranked form.

[14] A brief introduction to VIFs can be found at http://en.wikipedia.org/wiki/Variance_inflation_factor.

In the first two lines of panel B of Table 4 we report key percentiles of the absolute cross-correlations amongst the full set of 100 scaled decile ranked RPS, estimated both from pooled cross-section time-series data, and by month. In each case, the mean absolute cross-correlation is low (0.08 and 0.09, respectively) but the distribution is highly skewed by a few RPS, largely those with VIFs > 6.0 as reported in panel A.[15] The third line of panel B shows that after removing RPS with VIFs > 6.0, cross-correlations decline, most especially at the top end. Panel C visually describes the distribution of absolute cross-correlations after removing the nine RPS that per panel A have extreme collinearity based on their VIFs. The fact that panels B and C indicate that 75% of the absolute cross-correlations are less than 0.10 suggests that a large fraction of unidimensionally priced RPS will be multidimensionally priced (since almost all the RPS we include in our analysis were found to be significant in their originating research papers)—which is what we find to be the case.

3.4 Fama-MacBeth cross-sectional regressions of 1-month-ahead stock returns onto RPS

We measure the dimensionality in returns by estimating standard Fama and MacBeth (1973) regressions over the period 1980-2012 to determine how many and which RPS are priced when they are unidimensionally versus multidimensionally projected onto future 1-month ahead stock returns. We calculate the mean estimated slope coefficients on scaled decile ranked RPS and their associated t-statistics from the time-series of monthly cross-sectional regressions. When calculating t-statistics we employ Newey-West adjustments over 12 lags. We denote the annualized value of the monthly hedge returns represented by the estimated coefficients on scaled decile ranked RPS as the mean annualized long/short hedge returns (hereafter, MALSRets) of the RPS. Following the interpretation of the estimated coefficients as hedge portfolio returns, we propose that the MALSRet on a given RPS provides one measure of the raw economic significance of that RPS in the cross-section of expected returns. However, we emphasize that we do not view MALSRets as implementable by long/short practitioners over the window 1980-2012. Even setting aside transactions costs, realizing the level of in-sample MALSRets that we document would have required knowing about each and every RPS in real time; knowing the 1980-2012 multidimensional relations between every RPS and expected returns before the RPS were discovered and as of 1980; and having sufficient computer power, real-time data feeds and specialized human capital.

[15] Untabulated results show that the mean absolute cross-correlation amongst RPS is similarly small if cross-correlations are calculated before missing RPS values are reset to each RPS' monthly mean or if cross-correlations are calculated using normalized RPS rather than scaled-decile ranked RPS.

4. Main One-Month Ahead Return Dimensioning Results

4.1 Assessing the pricing of the conventional 3-dimensional set of firm size, book-to-market, and 12-month momentum in 1-month ahead returns during the period 1980-2012

We begin re-measuring of the dimensionality of U.S. monthly stock returns by benchmarking the conventional view that firm size *mve*, book-to-market *bm*, and 12-month momentum *mom12m* well describe the cross-section. In light of recent work by Fama and French (2013, FF13) in which Fama and French propose a five factor model to upgrade the widely used Fama and French (1996) three factor and Carhart (1997) four factor models, we also estimate the pricing of *mve*, *bm* and *mom12m* after adding operating profitability *roic* and investment *agr*. For the period 1980-2012, which overlaps only partially with the 1963-1990 window used by FF92, we estimate Fama-MacBeth regressions in which the dependent variable is 1-month ahead returns, and the independent variables are some or all of the scaled decile ranks of *mve*, *bm*, *mom12m*, *roic* and *agr*.[16] In doing so, our objective is to determining whether the signs and statistical significance of the relations between 1-month ahead returns and *mve*, *bm*, *mom12m*, *roic* and *agr* during 1980-2012 do or do not parallel those documented in the FF92, Jegadeesh (1990), Jegadeesh and Titman (1993), and FF13 papers.

Table 5 reports the results from the Fama-MacBeth regressions using all firms, and following Fama and French (1996) also large-cap, mid-cap, and small-cap firms separately. The predicted signs are those that are observed in FF92, Jegadeesh and Titman, and FF13. Large-cap firms are the largest 1,000 companies by market cap; mid-cap are the next largest 2,000; and small-cap are all remaining firms.[17] The mean monthly number of just over 5,000 firms is more than twice the 2,267 figure reported in FF92 because the number of firms in the CRSP and Compustat databases has grown substantially since the 1990 endpoint of the data window used by FF92.

The estimated coefficient signs and associated t-statistics for the all firm data that are reported in Panel A of Table 5 mostly conform with those reported in Table 3 of FF92. The estimated annualized coefficients are −4.1% for *mve* (t-statistic = −0.9), 13.2% for *bm* (t-statistic = 3.5), and 5.8% for *mom12m* (t-statistic = 5.8). Panel A confirms some but not all of FF92 and

[16] Following Fama and French (1996) and others, we define 12-month momentum as the cumulative returns calculated over the 11 months consisting of the prior 12 months except for the immediately preceding month.

[17] To create cutoffs for the largest 1,000 companies, we rank stocks by their month-end market cap. Since ties in the market cap cannot be ordered within the tied values, we assign the average ranking of the next lowest and next highest value of market cap to tied values. Thus, if there are 10 tied values and the next highest rank is 5 (so that the next lowest rank is 16), then the 10 tied values are assigned a rank of 10.5, the average of ranks 6-15. The assignment of ranks to tied values results in the cutoff for large firms, for example, being only approximately, not exactly, the largest 1,000 firms.

Jegadeesh and Titman's findings in that while *bm* and *mom12m* are reliably priced, the estimated coefficient estimate on *mve* is insignificantly different to zero.[18] A similar set of inferences are found in panels B and C where the set of RPS is expanded to include *roic* and *agr*. Namely*, bm, mom12m, roic* and *agr* are reliably priced with the same sign observed as in the original papers, but *mve* is not. Results for large-cap, mid-cap and small-cap firms reveal strong size-based differences. Of the 12 coefficients estimated across panels A, B and C for large-cap stocks, only three are reliably different from zero (one per panel) whereas 10 are reliably different from zero for small-cap stocks.

The results reported in Table 5 lead us to conclude that except for *mve*, the pricing over 1980-2012 of the conventional 3-dimensional RPS set of *mve*, *bm* and *mom12m*, and of the newer FF13-based augmented RPS set *mve*, *bm*, *mom12m*, *roic* and *agr* is confirmed, and that the economic and statistical strength of the pricing is far greater in small-cap firms than it is in large-cap firms.

4.2 Primary results on the number and identity of multidimensionally priced RPS

In Tables 6 and 7 we report the main findings of our paper, obtained by our extending the dimensioning of the cross-section of expected stock returns from the conventional set of *mve, bm* and *mom12m* focused on in Table 5 to the 20-to-30 fold larger and far more diverse set of 100 RPS detailed in Tables 1-2. Following the pattern established in Table 5, we report results for all firms taken together and for large-cap, mid-cap and small-cap firms separately. For all firms taken together, we first report the results of unidimensional regressions in which each pre-VIF-outlier-trimmed 100 RPS is singly projected onto future 1-month returns, and then multidimensional regressions in which all the post-VIF-outlier-trimmed 91 RPS are simultaneously projected onto 1-month ahead returns.

For each set of regressions detailed in Tables 6 and 7, we report the number of t-statistics that exceed in absolute value two t-statistic cutoffs, namely 1.96 and 3.0. We employ two cutoffs to speak to alternative ways of assessing the extent to which multidimensionality is present. On the one hand, an absolute t-statistic cutoff of 1.96 yields the number of significant RPS based on the conventional classical statistical hurdle.[19] On the other hand, Harvey, Liu and Zhu (2013, HLZ) justifiably criticize a cutoff of 1.96, arguing that it fails to take into account several kinds of snooping biases that exist in the RPS research and publication processes. In place of 1.96, they advocate that

[18] Chan, Karceski and Lakonishok (2000) and Horowitz, Loughran and Savin (2000) also find that *mve* appears less robustly related to future returns than indicated in FF92, mostly coming from a weakened relation after 1990.

[19] We note that a t-statistic cutoff of 1.96 may be seen as conservative in light of the fact that the prior literature yields one-sided sign predictions for the RPS.

authors, editors and readers of RPS papers apply a t-statistic cutoff of 3.0. While there may be reasons to suppose that a t-statistic cutoff of 3.0 might be too stringent,[20] we use 3.0 in order to try to avoid overstating the degree of multidimensionality in returns. For purposes of visual emphasis, we differentially color highlight by column the RPS that have an absolute t-statistic ≥ 3.0.

Inspection of panel A of Table 6 reveals several notable findings. First and foremost, for all firms combined, the first two rows of panel A indicate that 24 of the 91 RPS are reliably multidimensionally priced in the cross-section of 1-month ahead U.S. stock returns. This is an order of magnitude larger than *bm* and *mom12m* priced in panel A of Table 5, and almost three times that of the largest number of multidimensionally documented RPS in prior work (Lewellen, 2013, nine RPS with an absolute t-statistic ≥ 3.0). The mean adjusted R^2 of 6.0% is three times the 2.0% uniformly reported in panels A-C of Table 5 for the smaller RPS set *mve*, *bm*, *mom12m*, *roic* and *agr*. Thus, not only do we find that far more RPS are reliably multidimensionally priced than is conventionally presumed, but the much larger set of priced RPS explains much more cross-sectional variation in monthly returns. Taken together, the large number of multidimensionally priced RPS and the material fraction of return variance they explain run counter to the view that because financial data such as returns contain a lot of uncertainty, predictable patterns will be at best modest and very subtle (as argued by Hansen, 2013).

The second result we highlight in panel A of Table 6 is that just six RPS are multidimensionally priced in large-cap firms as compared to 20 in mid-cap firms and 21 in small cap firms. However, the far fewer RPS that are priced in large-cap firms explain two to four times the cross-sectional variation in returns as compared to the far larger number of RPS that are priced in mid-cap and small-cap firms. The six significant RPS and the greater explanation of the variation for large firms suggest that a smaller model such as a four RPS model might be more likely to provide a reasonable approximation of expected returns for large firms. However, we return in our discussion of Table 8 to the finding that the characteristics used in prior restricted models do not appear to completely overlap with the commonly used models.

Third, inspection indicates that multidimensionally priced RPS are not clustered by when they were discovered, nor are they predominantly accounting-based or finance-based. Untabulated

[20] For example, 39% of the 1980-2012 firm-months we use are post-publication. McLean and Pontiff (2013) show that mean unidimensioned RPS hedge returns decline by an average of 35% after being published. Since we use all firm-months equally in our Fama-MacBeth regressions, the MALSRets and associated t-statistics that we estimate are in actuality weighted averages of pre- and post-publication MALSRets and t-statistics.

results also show that similar and large numbers of RPS are multidimensionally priced in the 1980s, 1990s and 2000s decades that make up the full 1980-2012 data window.

In panel B of Table 6 we present a high level approach to comparing the pricing of RPS when measured unidimensionally versus multidimensionally. Specifically, we report the results of regressing the vector of MALSRets from multidimensioned projections of RPS onto 1-month ahead returns on the vector of MALSRets from unidimensioned projections of the same RPS, and likewise for the associated t-statistics. Our goal is to assess the degree to which the coefficients and t-statistics on RPS reported in prior research may be economically and statistically upwardly biased in absolute magnitude because they were measured in a manner that is closer to being unidimensional than multidimensional.[21] The results reported in panel B indicate that on average, the MALSRets earned by multidimensioned RPS are one half to two thirds smaller than those of unidimensioned RPS, and that the t-statistics on multidimensioned MALSRets are one half those on unidimensioned MALSRets. Stated differently, absent conditioning information, a unidimensioned RPS with a mean hedge return of 12% per year and a significant associated t-statistic of 3.0 should more accurately be characterized as a multidimensioned RPS with a smaller mean hedge return of 4.9% (12% x 0.41) and an insignificant t-statistic of 1.74 (3.0 x 0.58).

The results presented in Table 6 warrant some caveats regarding the interpretations we make. As shown in panel A, we note that 35 (48) t-statistics are significant at a 3.0 (1.96) cutoff level in the unidimensional regressions. Thus, after aligning all the RPS in calendar time, using all companies and evaluating the empirical relations using the full time period 1980-2012, some 50% of RPS are significantly related to 1-month ahead returns before they are put into competition with each other via a multidimensional regression. This may reasonably be seen as surprising because almost all the RPS we employ have been reported as being statistically significant in their originating studies[22]. However, we choose not to iteratively adjust our alignment methodology so to achieve a larger number of unidimensional statistical significance because such efforts are at the heart of concerns about in-sample data snooping (Harvey, Liu and Zhou, 2013). We do so because we argue that the approach we take reasonably balances overfitting concerns with seeking to powerfully measure the

[21] We acknowledge that the unidimensional regressions we estimate in which each pre-VIF-outlier-trimmed 100 RPS is singly projected onto future 1-month returns do not exactly replicate the approach taken in prior RPS papers in that we do not control for any of the 'risk factors' that such papers commonly do control for. However, Green, Hand and Zhang (2013) report that of the 91 % of RPS papers that do orthogonalize against at least one risk factor or firm-specific characteristic, just 12 % orthogonalize against something other than one or more of beta, size, book-to-market, and 12-month momentum (or their factor returns), and very few orthogonalize against all four.

[22] Exceptions such as *beta* arise from their inclusion in prior papers based on their theoretical or historical interest.

true dimensionality of returns. Nevertheless, the unidimensional results reported in panel A of Table 6 indicate that a large number of RPS results in prior research are sensitive to small changes in measurement and/or time periods. In a sidebar manner, we conclude that some of the concerns raised by other researchers about in-sample over-fitting seem justified (McLean and Pontiff, 2013). Given our unidimensional results, we propose that it is then even more striking that we find 24 significant t-statistics in the multidimensional regressions given the 35 that we find significant in the unidimensional regressions; i.e., 24/35 is much larger than 24/91.

The results in Table 6 are obtained using the scaled decile ranks of the RPS variables. However, there is a potential concern that in using this ranking approach we are discarding important information from the RPS variables or are imposing an undesirable property on the RPS. Some prior research has found that the properties of certain RPS-return relations are not well understood. For example, Fama and French (2008) find evidence of non-linearities in some RPS-return relations. To address this concern and generalize our results, in Table 7 we therefore report the results of re-estimating Table 6's regressions using normalized RPS in place of scaled decile ranked RPS[23]. Normalized RPS are also often employed by quantitative-oriented investment practitioners. We compute normalized RPS monthly by winsorizing each RPS as described previously and then standardizing the RPS to have a zero mean and unit variance. Estimated coefficients are shown X100 and then X12, making them the annualized percent returns accruing to a one standard deviation increase in the individual RPS.

A comparison of the detailed results reported in Tables 6 and 7 demonstrates that the degree of multidimensionality in returns and their explanatory power is not sensitive to whether RPS are measured in scaled decile ranked or normalized form. For all firms combined, the first two rows of panel A of Table 7 indicate that 28 of the post-VIF-outlier-trimmed set of 91 normalized RPS are reliably multidimensionally priced in the cross-section of 1-month ahead U.S. stock returns, as compared to 24 for scaled decile ranked RPS. Likewise, the mean multidimensioned regression adjusted R^2 for all firms combined is 7.0% for normalized RPS versus 6.0% for scaled decile ranked RPS. It is also the case that on average there is a strongly positive relation between the RPS that are estimated to be multidimensionally priced when RPS are measured in scale decile ranked form, and the RPS that are estimated to be multidimensionally priced when RPS are measured in normalized form. In panel B of Table 7 we report that the Pearson correlations between the t-statistics on the

[23] Given the large number of RPS we study, we view it as infeasible to examine non-linearities in RPS-returns relations in the manner undertaken in Fama and French (2008).

multidimensioned mean coefficient estimates from scale decile ranked versus normalized RPS are 0.77 for all firms, and 0.81, 0.79 and 0.81 for large-cap, mid-cap and small-cap firms, respectively. This said, we note that the significance of some highly cited RPS depends on how RPS are measured. For example, for all firms combined, firm size *mve* (RPS #4) and Sloan (1996) accruals *acc* (RPS #36) are insignificantly multidimensionally priced when they are measured in scaled decile ranked form, but are reliably negative multidimensionally priced when they are measured in a normalized manner. It is also the case that share turnover *turn* (RPS #37) and dollar trading volume in month t-2 *dolvol* (RPS #46) are highly significant when measured in scaled decile rank form (for all firms, t-statistics are 10.0 and -9.3, respectively), but are insignificant when measured in normalized form (for all firms, t-statistics are 1.0 and 0.1, respectively).

The final view we provide regarding the number and identity of multidimensionally priced RPS is reported in Table 8, where we identify the largest ten t-statistics (and Sharpe ratios) in absolute magnitude for each of the regressions reported in each of Tables 6 and 7.[24] Immediately below the listing of these ten largest t-statistics, we report for the all firms dataset the unidimensional and multidimensional ranking out of 91 of each of *bm*, *mve* and *mom12m*, and for each of the large, mid and small cap datasets the t-statistic on *bm*, *mve* and *mom12m* in those regressions. Our purpose in Table 8 is to measure the degree to which *bm*, *mve* and *mom12m* do or do not remain the most powerful RPS in explaining 1-month ahead U.S. stock returns after the set of evaluated RPS is greatly expanded, in both the marginal statistical and marginal economic senses of the word.

The results reported in Table 8 indicate that firm size, book-to-market, and 12-month momentum only infrequently place in the largest ten t-statistics of multidimensioned RPS. For example, for all firms combined, *bm*, *mve* and *mom12m* are ranked 15th, 52nd and 70th and in panel B they are ranked 27th, 7th and 39th, respectively. For the regressions estimated separately on large, mid and small-cap firms, out of the 51 absolute value t-statistics $\geq$ 3.0 shown, only three pertain to *bm*, *mve* or *mom12m*. Untabulated results also indicate that *roic* and *agr* do not place in the largest 10 t-statistics in any of the regressions.

We caution against our results automatically being seen as a new and better workhorse model for expected monthly U.S. stock returns because we argue that there is yet much to understand about the multidimensional results we report. For example, in an initial attempt to understand which types

[24] In our situation, the RPS' Fama-MacBeth t-statistic is 5.8 times the RPS' Sharpe ratio. Given monthly data over 1980-2012 and serially uncorrelated coefficient estimates, the Sharpe ratio of an RPS with a Fama-MacBeth t-statistic of t* is obtained by multiplying t* by the square root of 12 (the number of months in a year) and dividing it by the square root of 396 (the number of months in the 33-year period 1980-2012).

of RPS matter, we note that inspection of the lists reported in Table 8 suggests that there may be common themes among the RPS with the largest t-statistics, but also that these themes vary by firm size in ways that warrant further research. First, fundamental valuation type measures and market trading type measures appear to matter across firm size. In large-cap firms the important RPS can be broadly classified as fundamental valuation measures (*sfe, ep, cash,* and *bm*) or trading type measures (*retvol*). For mid-cap and small-cap firms the themes appear slightly different. For example, most of the fundamental type RPS that are important in mid-cap and small-cap firms are changes type or momentum type measures (*ear, rsup, sue*), and the number of trading type RPS is greater (*turn, dolvol, retvol*).

4.2 Robustness tests on the multidimensionality in returns

In this section we present evidence that confirms the high degree of dimensionality in returns using a variety of approaches including factor analysis of the RPS themselves, factor analysis of long/short hedge returns obtained from the RPS, LASSO regression, out-of-sample RPS hedge portfolio returns, and regressions of portfolio returns on RPS factor portfolio returns. We undertake these robustness tests because we recognize that it may be that the results in Tables 6 and 7 reflect the spurious fitting of noise, rather than the presence of robust statistical and economic phenomena.

4.2.1 Statistical factor analysis of RPS and long/short RPS hedge returns

In Figure 2, for all firms and using pooled cross-section time-series data on the full set of 100 RPS measured in scaled rank decile form, we report the results of factor analyzing via principal components analysis the RPS themselves (panel A), and RPS-weighted long/short RPS hedge returns (panel B). Figure 2 graphs the variance explained by each statistical factor for the statistical factors with eigenvalues > 1. Panel A reveals that 29 RPS factors have eigenvalues > 1, a number that lies between the 24 and 46 RPS that we report in panel A of Table 6 have absolute t-statistics of ≥ 3.0 and ≥ 1.96, respectively. The declining pattern shown in panel A indicates that each additional statistical factor explains less of the total variation in RPS but that each additional statistical factor continues to add additional information about the total variation. In panel B we show that 14 factors derived from principal component analysis of the RPS-weighted hedge returns from individual RPS have eigenvalues > 1, so that while there exist fewer statistical factors of the hedge returns, statistically there are 14 different significant factor-type determinants of 1-month ahead returns. In

Panel B, the RPS weighted hedge returns are created by summing the weight times the return across firms to create a hedge portfolio return where the weight w_{it} applied to firm *i* is given by:

$$w_{it} = 2\left[\frac{RPS_{it} - 0.5}{\sum_{i=1}^{Nfirms_t} abs\{RPS_{it} - 0.5\}}\right]$$

RPS in the weight calculation is the scaled decile rank RPS so that the RPS is scaled 0 to 1. This hedge return then measures the return to a portfolio that holds long positions in half of the firms and short positions in half of the firms with weights increasing towards the extremes of the RPS variable.

Both panels of Figure 2 support the conclusion that there is high dimensionality in the underlying RPS themselves, supporting the view that the high dimensionality we documented in Tables 6 and 7 cannot be linearly collapsed down to a small number of latent factors. This contrasts with research that has found only a small number of statistical factors in realized returns (Brown, 1989; Connor and Korajczyk, 1993).

4.2.2 LASSO regressions

In Table 9 we next report the results of estimating a least absolute shrinkage and selection operator (LASSO) regression to select the RPS that incrementally explain 1-month ahead returns.[25] LASSO constrains the absolute magnitude of regression coefficient estimates, with the potential benefit that by doing so, the abnormally large coefficients that can occur when there exists high collinearity among all or some of the set of independent variables are avoided. In addition, because LASSO constrains that absolute magnitude of the coefficient estimates, it can result in coefficient estimates equal to zero and as such LASSO 'naturally' becomes a model selection method as well. We note that the number of RPS that LASSO selects depends on the constraints placed on the magnitudes of the coefficients. In this regard we follow Efron, Hastie, Johnstone and Tibshirani (2004) and select the best model from all values of the constraint, based on using the smallest value of Mallow's Cp criterion.

Table 9 indicates that using monthly mean-adjusted returns on the pooled sample of data, LASSO regression applied to the full set of 100 scaled decile ranked RPS yields a similar degree of multidimensionality in 1-month ahead returns to that documented in Tables 6 and 7. Specifically, LASSO selects 19 RPS for all firms combined, and 13, 18 and 18 for large, mid and small-cap firm-

[25] Our thanks to Matt Bloomfield for suggesting the use of LASSO. A description of the LASSO method can be found at http://statweb.stanford.edu/~tibs/lasso/simple.html.

size groupings. For simplicity we report only the set of RPS selected by the LASSO procedure. Untabulated results for estimated coefficients and significance levels based on this LASSO-selected model are comparable to those already presented.

4.2.3 Out-of-sample RPS hedge portfolio returns

The final method we use to validate the high dimensionality of returns is out-of-sample return prediction. This test is similar in spirit to Lewellen (2012), a study that provides important insight into the question about whether including more RPS into models of the cross-section of returns is valuable from an out-of-sample perspective. In principle, if models of the cross-section of returns are merely the result of in-sample overfitting of the data, then they should perform no better, or should perform worse, than simpler models that capture real economic relations. We therefore conduct a similar set of out-of-sample tests.

For each month beginning Jan. 1990, we use a window consisting of 120 months of trailing data to estimate the coefficients of three sets of scaled decile ranked RPS: [1] *mve*, *bm* and *mom12m* (denoted FF1); [2] *mve*, *bm*, *mom12m*, *roic* and *agr* (denoted FF2); and [3] the 91 RPS that underpin the multidimensional tests reported in Tables 6 and 7 (denoted ALL). Over the estimation window, the return variable used to estimate the models is the monthly mean-adjusted return leading to the estimation of expected relative returns by allowing for differences in intercepts across months. To arrive at inferences that are less likely to be infeasible from a practitioner point of view, we exclude small-cap firms and limit the data to approximately 3,000 per month large- and mid-cap firms. We then project the estimated coefficients onto the RPS in place at the end of the estimation window to create a firm-specific predicted relative return $pret_{it}$ for firm *i* in month *t* immediately following the estimation window. We combine the realized returns for that same month into an overall hedge portfolio return where the weight w_{it} applied to firm *i* is given by:

$$w_{it} = 2\left[\frac{pret_{it}}{\sum_{i=1}^{Nfirms_t} abs\{pret_{it}\}}\right]$$

This weighting scheme yields an approximately equally long-short standard 2X gross levered out-of-sample hedge portfolio return for month t for each of the three sets of RPS with larger long and short weights on the most extreme predicted returns.[26] We acknowledge that while there is certainly an in-sample aspect of our approach (since we use RPS that in most cases were identified during the out-of-sample period), the predicted hedge returns $pret_{it}$ are based only on information available in real-time. Moreover, in our rolling window estimations we do not discard any RPS even when evidence might suggest that one or more RPS are no longer reliably priced.

We present out-of-sample RPS hedge portfolio returns in order to test the hypothesis that if the Fama-MacBeth regression coefficient estimates obtained via the estimation period represent either the fitting of noise or real but unstable relations between RPS and future returns, then we will expect to see small mean out-of-sample hedge portfolio returns and/or poor Sharpe ratios. However, such a conclusion is strongly rejected by the results we report in Figure 3. Most particularly, panel A of Figure 3 shows that the mean out-of-sample return earned during 1990-2012 by the ALL portfolio of RPS is 2.1% per month or 28% per year. In combination with the fact that the annualized ALL Sharpe ratio of 2.58 is more than twice that earned by the FF1 and FF2 portfolios of far fewer RPS, we conclude from the results in Figure 3 (and from the other robustness tests described in sections 4.1.1-4.2.3) that the high degree of dimensionality that we document in Tables 6 and 7 to be present in the cross-section of expected U.S. monthly stock returns is real, and not a statistical artifact.[27]

4.2.4 RPS factor portfolio returns

An important alternative approach used in studying cross-sectional variation in stock returns is factor portfolio returns analysis (e.g., Fama and French, 1996). In light of this, we seek to provide preliminary evidence on whether the high RPS-based multidimensionality in returns is also present in the factor structure of returns.

Every month, for each of the 100 RPS listed in Table 1, we rank firms into deciles. Then, every month and for each RPS decile we create an equally-weighted RPS decile portfolio return using returns in the subsequent month. This yields a time series of monthly portfolio returns for each of the 1,000 RPS deciles. For each RPS decile, we then estimate a time series regression of that RPS

[26] We observe similar and slightly stronger results when we rank predicted returns into deciles and form portfolios on only the extreme deciles of the predicted returns.

[27] We posit that one reason why we find better out-of-sample performance for the ALL model over the restricted FF1 and FF2 models is that we include more timely RPS in the ALL model. Fama and French (1992, 1996, 2008, 2013) make the conservative decision to use stale RPS measurements that avoid short term price fluctuations. In untabulated results we find that the largest contributor to the improved out-of-sample performance for the ALL model comes from those RPS that are measured on a more frequent (= monthly) basis. However, even when we include only RPS that are measured at the same frequency as FF1 and FF2, we find that the stale-only-ALL model does better in terms of cumulative returns and Sharpe ratios than FF1 and FF2.

decile's monthly portfolio returns on the factor returns pertinent to one of four alternative models: [1] the equally-weighted market EW; [2] EW and the long/short hedge portfolio factor returns to market cap, book-to-market and 12 month momentum; [3] EW and the factor returns to market cap, book-to-market, profitability and asset growth; [4] a model that selects the five factor returns from the full set of 100 factor returns (one factor return per RPS) that yields the highest time series regression adjusted R^2 for that RPS decile. Once the time series regressions are estimated, for each RPS we calculate the mean absolute value of the regression intercepts and the mean adjusted R^2 across the 10 deciles.

We begin with model [1] for obvious reasons. Model [2] is the classic factor model proposed by Carhart (1997) and model [3] is a five-factor model recently proposed by Fama and French (2013). In its unrestricted form (i.e., without specifying in advance the number of factors that are selected), Model [4] is new to the factor return literature in that it allows the data to determine how many and which factors drive returns (depending on the statistical factor identification criteria chosen by the researcher). The approach flexibly allows each RPS decile to be empirically associated with a potentially different number and type of factors.[28] In our study we specify that the number of factors included is five because doing so enables us to calibrate the extent to which the resulting 1,000 sets of five factors do or do not overlap with the factors that are most prominent in the existing asset pricing literature. Following Carhart (1997) and Fama and French (2013) we take these to be the equally-weighted market, the factor returns to market cap, book-to-market, 12-month momentum, profitability and asset growth.[29]

In panel A of Table 10, for each of factor models [1] – [4] we report descriptive statistics on the distribution of 100 mean absolute intercepts and 100 adjusted R^2 (one per RPS) obtained by from the time series factor return regressions. Panel A shows that while the equally-weighted market return model [1] explains by far and away explains the lion's share of returns with a mean adjusted R^2 of 92%, it also yields the largest absolute monthly return intercept of all four models, namely 0.25%. Models [2] and [3] are more powerful than the equally weighted market alone in that each yields a smaller absolute intercept and a larger adjusted R^2. Model [4] is the most impressive, with

[28] It should be noted that including the long/short hedge portfolio factor returns for all 100 RPS as explanatory variables in time series regressions where the number of observations (months) in each regression is 396 results in a small number of observations per estimated parameter, and the possibility that the chosen set of factors to be highly cross-correlated with each other.

[29] We do not pursue the conventional approach used in factor return studies of sorting all RPS and forming portfolios based on 2-way, 3-way, 4-way, …, 100-way sorts because we judge that such an approach would rapidly become infeasible.

an adjusted R2 of 97% (5% larger than that of model [1]), and a mean absolute intercept of 0.12% that is less than half that of model [1] and one third smaller than models [2] and [3].

In panel B of Table 10 we report the frequency with which either certain prominent individual factors, or a particular full set of such factors, are present in or entirely comprise the five factors selected in the 1,000 RPS decile factor regressions. Not surprisingly, we find that the market return per se (= model [1]) is one of the factors in 51% of the 1,000 sets of five factors estimated in our 1,000 factor regressions. It is also the case that each of the firm size, book-to-market, 12-month momentum, profitability and asset growth factors are present, although with much smaller frequencies that range from 2% for 12-month momentum to 17% for firm size. What is more surprisingly, however, is that neither the set of factors in the Carhart (1997) four-factor model (= model [2]) nor the set of factors in the Fama and French (2013) five factor model (= model [3]) are ever present in the 1,000 sets of five factors estimated in our 1,000 factor regressions.

5. Implications of Multidimensionality for Academic and Practitioner Research

In this section we present some of the implications that we propose that our study may have for past and future research that is focused on, or uses, monthly U.S. stock returns.

The first and most important of implication is that prior research has focused on too few RPS, and on RPS that are empirically distant from what are actually the most important RPS. Not only are there almost ten times the RPS that matter in the cross-section of future monthly stock returns than firm size, book-to-market and 12 month momentum, and not only does the full set of multidimensioned RPS explain between three and nine times the cross-sectional variation as firm size, book to market and 12 month momentum, but the most important RPS (as judged by their multidimensioned t-statistics) are not firm size, book-to-market and 12 month momentum, but rather well known RPS such as unexpected quarterly earnings as well as underappreciated RPS such as 12 month industry return momentum and trading volume. We therefore propose that there is likely to be substantial value to future research seeking to understand why stock returns are so highly dimensional, why the most empirically important RPS are priced the way they are, and what kinds of market efficiency or inefficiency are consistent with the level of return dimensionality that we document. We see little mileage in discovering new RPS before insight is gained into the large number of RPS that have already been discovered.

In critiquing the conventional RPS set of firm size, book-to-market and 12-month momentum, we recognize and seek to address the valid question of "If not firm size, book-to-market and 12-month momentum, what then should academics and practitioner use in research that employs 1-month ahead U.S. stock returns, given that it seems clumsy to include all of the 24+ RPS that we find to be statistically significant in our study?" We do so because much academic and practitioner work requires a model of firm-specific expected returns and/or controls for those firm characteristics that are associated with realized returns.

After acknowledging that we do not have a definitive answer to this important question, we put forward for academic and practitioner consideration a distilled RPS model that consists of the following 10 RPS: asset growth *agr*, book-to-market *bm*, dollar trading volume *dolvol*, quarterly earnings announcement returns *ear*, 12-month industry-adjusted returns *indmom*, 36 month momentum *mom36m*, quarterly return on assets *roaq*, forecasted annual earnings *sfe*, unexpected quarterly earnings *sue*, and share turnover *turn*.[30] The exact definitions of these RPS can be found in Table 2. We arrived at our distilled model by fixing the number of RPS at 10, and then determining within a pooled time-series cross-sectional regression model which 10 RPS most powerfully describe the cross-section of 1-month ahead U.S. stock returns over the period Jan. 1980-Dec. 2012 in the sense of yielding the highest adjusted R^2 statistic.

We assess the closeness of the empirical fit of the distilled 10 RPS model to the totality of the information available in the 91 RPS we analyze earlier in the paper by computing the quasi out-of-sample performance of the distilled 10 RPS model. The results are reported in Figure 4. Figure 4 shows that the distilled 10 RPS model (denoted TEN in Figure 4) performs well, coming close to the cumulative return performance achieved by the ALL RPS model.[31] As such, the distilled 10 RPS model would seem to offer interested academics and practitioners with a powerful yet not overly cumbersome way of modeling firm-specific expected returns and/or controlling for the main firm characteristics that are associated with realized returns.

The second implication we propose that our study holds is that a sizeable number of past papers that have inferred that a particular newly discovered RPS is statistically and/or economically significant may have been mistaken, at least with regard to the generalizability of their inference over the 1980-2012 period we study. Using the data-snooping-adjusted t-statistic of 3.0 proposed by Harvey, Liu and Zhu (2013), and even though RPS are only weakly cross-correlated, we find that

[30] We note that the 10 RPS in the distilled model span both financial statement and price data, as well as lower and higher frequency signals.

[31] Untabulated results also indicate that from a factor return perspective, one or more of the 10 RPS in the distilled RPS model are also present in some of the 1,000 sets of five factors estimated in the 1,000 factor regressions described in section 4.2.4.

approximately 75% of the large set of RPS we study are not multidimensionally priced and that a substantial number are not unidimensionally priced. Moreover, our finding that the hedge returns earned by multidimensioned RPS are on average one half to two thirds smaller than those earned by unidimensioned RPS implies that the economic importance of any given RPS—when appropriately measured at the margin after controlling for the economic importance of other RPS—is likely to be much smaller than previously thought. Moreover, the uncertainty that our paper implies for the robustness and validity of the inferences made by prior RPS papers as to the true novelty of the RPS they study is separate from, but additive to, the concern expressed by Harvey, Liu and Zhu's (2013) that the t-statistics found in prior RPS research suffer from a variety of data snooping biases and therefore warrant a substantial haircut by readers.

Our third takeaway is that the true dimensionality in returns is likely larger than we have estimated. Although we study the largest number of RPS yet in the academic literature, the 100 RPS we evaluate represent less than one third of the 330+ RPS that have been publicly identified by business academics (Green, Hand and Zhang, 2013; Harvey, Liu and Zhu, 2013). Moreover, the replicable but often necessarily crude choices we make to combine RPS across companies and time periods and databases, our using only those RPS that can be calculated from CRSP and Compustat and I/B/E/S, our approach to dealing with missing data, and our measuring the average of pre- and post-publication relation all serve to hinder, not help, us measure RPS to the same accuracy as in the originating RPS papers and therefore the form of the signals reacted to and priced by investors.

Last, but not least, we suggest that the high return dimensionality we document draws attention to the gap between academic finance research and investment practice. While a small number of RPS have dominated the academic literature as benchmarks for expected returns, in the practitioner sphere, large and sophisticated quantitative investors such as Axioma, BGI/BlackRock, Jacobs-Levy Equity Management, MSCI/Barra, Northfield and JP Morgan (to name but a few) have successfully developed and used equity models that contain far more factors than firm size, book-to-market and momentum for many years. We therefore argue that our study highlights the need for greater connectedness between academics and practitioners, and the potential value of research focused on the empirical regularities that are relied on by investment professionals. To the best of our knowledge, practitioners only infrequently have strong theoretical foundations for why they include a multitude of RPS in their return prediction and risk management models, relying instead on the practical objective of using models that work in real-world equity investing. Moreover, for financial and legal reasons practitioners rarely publicly disclose the precise details or "secret sauce" in their multifactor equity models, especially in a timely manner. This stands in sharp contrast to academics who typically place their research into the public domain in a rapid manner.

6. Limitations of our Study

In this section we draw the reader's attention to several limitations of our paper. One of the most important is that even though our paper is the first to study the multidimensional pricing of a large number of RPS in the U.S. stock market, the set of 100 RPS that we use is only a portion of the full population of the RPS that have been documented by business scholars (Green, Hand and Zhang, 2013; Harvey, Liu and Zhu, 2013). Our cost-benefit calculus, combined with a desire to easy replicability of our results, led us not to include RPS that require proprietary or specialized data to calculate, or RPS that employ infrequent events. As such, we acknowledge that the degree of dimensionality we document, and the particular RPS that we estimate to be multidimensionally priced in a particular future return horizon, are likely understated and subject to change by more complete or advanced analysis by other scholars.

Our results are also dependent on the particular data and methodologies we use. To address concerns that our findings are sensitive to these choices, in untabulated tests we assessed the robustness of our results to several alternative variable measurements and research design choices. For example, in untabulated analyses we find that our major results and the inferences about the multidimensionality of stock market returns that we draw from them are robust to not infilling as many missing observations, using scaled decile ranks that condition on firm size, using firm size classifications based on a simple partitioning into the largest to smallest one third of firms, and using WLS in Fama-MacBeth regressions. Our results are also robust in their major aspects to including the nine highly cross-correlated RPS that we excluded in the majority of our tests.

Despite the robustness of the main conclusions of the paper, we do note that some individual RPS results are sensitive to the methodologies we use. Apart from Fama and French (2008) and Kraft, Leone, and Wasley (2006) we are unaware of studies that examine the sensitivity of reported anomalies to methodological changes, and in those particular cases to non-linearities in the return-RPS relation. The sensitivity of these relations suggests that either researchers have yet to understand the nature of these relations, or the relations that have been uncovered are somewhat less robust than conventionally assumed.

7. Conclusions

In this paper, 20+ years after Fama & French's seminal 1992 study, we have re-measured the dimensionality of the cross-section of expected U.S. monthly stock returns. Our motivation for doing so centered around Cochrane's 2010 AFA Presidential Address in which he issues a 'multidimensional challenge' and calls for Fama and French's 'anomaly digestion exercise' to be repeated in light of the hundreds of return predictive signals (RPS) that have been identified by business academics over the past 40 years.

We found that over the period 1980-2012, the dimensionality of monthly U.S. stock returns is almost 10 times that originally estimated by Fama and French. Of the 100 previously document RPS that we study, 24 are reliably multidimensionally priced, as defined by their mean coefficient estimate having an absolute t-statistic ≥ 3.0 in Fama-MacBeth regressions where all 100 RPS are simultaneously projected onto 1-month ahead returns. We confirmed the high degree of dimensionality in returns in a number of triangulating ways, including factor analysis of RPS, factor analysis of long/short RPS hedge returns, LASSO regression, regressions of portfolio returns on RPS-factor-mimicking-portfolio returns, and out-of-sample RPS hedge portfolio returns.

Among its chief supplementary results, our study shows that commonly used factors, such as size, book-to-market, and 12-month price momentum often miss economically important aspects of the cross-section of stock returns. Instead, we observe that firm characteristics such as earnings yield, recent earnings announcement returns, industry-adjusted momentum, stock turnover and unexpected quarterly earnings better explain the cross-sectional variation of stock returns. Empirically, we document that a distilled model with ten RPS captures a large fraction of the total information about future monthly U.S. returns present in the 100 RPS we study. As such, an empirical model based on these 10 RPS is likely to be much closer to the multidimensional models used by many large and sophisticated quantitative investors, and may serve as a better model of expected U.S. monthly stock returns for academics than the default Carhart four factor or new Fama-French five factor return models.

In conclusion, we believe that our findings point to the importance of continuing to understand the cross-sectional structure of returns. Given the large number of RPS that have already been documented in the literature and the high degree of multidimensionality we empirically find to be present in returns, we propose that an important avenue for future research is to understand why, when, and how returns are so multidimensional, before seeking to uncover yet more RPS.

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TABLE 1

Return predictive signals (RPS) used in the study, listed by publication or working paper year

#	RPS	Acronym	Author(s)	Date, Journal
1	Beta	*beta*	Fama & MacBeth	1973, JPE
2	Beta squared	*betasq*	Fama & MacBeth	1973, JPE
3	Earnings-to-price	*ep*	Basu	1977, JF
4	Firm size (market cap)	*mve*	Banz	1981, JFE
5	Dividends-to-price	*dy*	Litzenberger & Ramaswamy	1982, JF
6	Unexpected quarterly earnings	*sue*	Rendelman, Jones & Latane	1982, JFE
7	Change in forecasted annual EPS	*chfeps*	Hawkins, Chamberlin & Daniel	1984, FAJ
8	Book-to-market	*bm*	Rosenberg, Reid & Lanstein	1985, JPM
9	36-month momentum	*mom36m*	De Bondt & Thaler	1985, JF
10	Forecasted growth in 5-year EPS	*fgr5yr*	Bauman & Dowen	1988, FAJ
11	Leverage	*lev*	Bhandari	1988, JF
12	Current ratio	*currat*	Ou & Penman	1989, JAE
13	% change in current ratio	*pchcurrat*	Ou & Penman	1989, JAE
14	Quick ratio	*quick*	Ou & Penman	1989, JAE
15	% change in quick ratio	*pchquick*	Ou & Penman	1989, JAE
16	Sales-to-cash	*salecash*	Ou & Penman	1989, JAE
17	Sales-to-receivables	*salerec*	Ou & Penman	1989, JAE
18	Sales-to-inventory	*saleinv*	Ou & Penman	1989, JAE
19	% change in sales-to-inventory	*pchsaleinv*	Ou & Penman	1989, JAE
20	Cash flow-to-debt	*cashdebt*	Ou & Penman	1989, JAE
21	Illiquidity (bid-ask spread)	*baspread*	Amihud & Mendelson	1989, JF
22	1-month momentum	*mom1m*	Jegadeesh	1990, JF
23	6-month momentum	*mom6m*	Jegadeesh & Titman	1990, JF
24	12-month momentum	*mom12m*	Jegadeesh	1990, JF
25	Depreciation-to-gross PP&E	*depr*	Holthausen & Larcker	1992, JAE
26	% change in depreciation-to-gross PP&E	*pchdepr*	Holthausen & Larcker	1992, JAE
27	Industry-adjusted firm size	*mve_ia*	Asness, Porter & Stevens	1994, WP
28	Industry-adjusted cash flow-to-price ratio	*cfp_ia*	Asness, Porter & Stevens	1994, WP
29	Industry-adjusted book-to-market	*bm_ia*	Asness, Porter & Stevens	1994, WP
30	Annual sales growth	*sgr*	Lakonishok, Shleifer & Vishny	1994, JF
31	Industry-adjusted change in employees	*chempia*	Asness, Porter & Stevens	1994, WP
32	New equity issue	*IPO*	Loughran, Ritter & Ritter	1995, JF
33	Dividend initiation	*divi*	Michaely, Thaler & Womack	1995, JF
34	Dividend omission	*divo*	Michaely, Thaler & Womack	1995, JF
35	Sales-to-price	*sp*	Barbee, Mukherji & Raines	1996, FAJ
36	Working capital accruals	*acc*	Sloan	1996, TAR
37	Share turnover	*turn*	Datar, Naik & Radcliffe	1998, JFM
38	% change in sales - % change in inventory	*pchsale_pchinvt*	Abarbanell & Bushee	1998, TAR
39	% change in sales - % change in accounts receivable	*pchsale_pchrect*	Abarbanell & Bushee	1998, TAR
40	% change in CAPEX - industry % change in CAPEX	*pchcapx_ia*	Abarbanell & Bushee	1998, TAR
41	% change in gross margin - % change in sales	*pchgm_pchsale*	Abarbanell & Bushee	1998, TAR
42	% change in sales - % change in SG&A	*pchsale_pchxsga*	Abarbanell & Bushee	1998, TAR
43	# of consecutive earnings increases	*nincr*	Barth, Elliott & Finn	1999, JAR
44	Industry momentum	*indmom*	Moskowitz & Grinblatt	1999, JF
45	Financial statements score	*ps*	Piotroski	2000, JAR
46	Dollar trading volume in month t-2	*dolvol*	Chordia, Subrahmanyam & Anshuman	2001, JFE
47	Volatility of dollar trading volume	*std_dolvol*	Chordia, Subrahmanyam & Anshuman	2001, JFE
48	Volatility of share turnover	*std_turn*	Chordia, Subrahmanyam & Anshuman	2001, JFE
49	Scaled analyst forecast of one year ahead earnings	*sfe*	Elgers, Lo & Pfeiffer	2001, TAR
50	# of analysts covering stock	*nanalyst*	Elgers, Lo & Pfeiffer	2001, TAR

TABLE 1 (continued)

Return predictive signals (RPS) used in the study, listed by publication or working paper year

#	RPS	Acronym	Author(s)	Date, Journal
51	Dispersion in forecasted eps	*disp*	Diether, Malloy & Scherbina	2002, JF
52	Changes in inventory	*chinv*	Thomas & Zhang	2002, RAS
53	Idiosyncratic return volatility	*idiovol*	Ali, Hwang & Trombley	2003, JFE
54	Growth in long term net operating assets	*grltnoa*	Fairfield, Whisenant & Yohn	2003, TAR
55	RD_increase	*rd*	Eberhart, Maxwell & Siddique	2004, JF
56	Corporate investment	*cinvest*	Titman, Wei & Xie	2004, JFQA
57	Taxable income to book income	*tb*	Lev & Nissim	2004, TAR
58	Cash flow-to-price	*cfp*	Desai, Rajgopal & Venkatachalam	2004, TAR
59	Earnings volatility	*roavol*	Francis, LaFond, Olsson & Schipper	2004, TAR
60	Change in long-term debt	*lgr*	Richardson, Sloan, Soliman & Tuna	2005, JAE
61	Change in common shareholder equity	*egr*	Richardson, Sloan, Soliman & Tuna	2005, JAE
62	Illiquidity	*ill*	Acharya & Pedersen	2005, JF
63	# of years since first Compustat coverage	*age*	Jiang, Lee & Zhang	2005, RAS
64	Financial statements score	*ms*	Mohanram	2005, RAS
65	Price delay	*pricedelay*	Hou & Moskowitz	2005, RFS
66	R&D-to-sales	*rd_sale*	Guo, Lev & Shi	2006, JBFA
67	R&D-to-market cap	*rd_mve*	Guo, Lev & Shi	2006, JBFA
68	Return volatility	*retvol*	Ang, Hodrick, Xing & Zhang	2006, JF
69	Industry sales concentration	*herf*	Hou & Robinson	2006, JF
70	% change over two years in CAPEX	*grcapex*	Anderson & Garcia-Feijoo	2006, JF
71	Zero-trading days	*zerotrade*	Liu	2006, JFE
72	Change in 6-month momentum	*chmom*	Gettleman & Marks	2006, WP
73	Return on invested capital	*roic*	Brown & Rowe	2007, WP
74	Abnormal volume in earnings announcement month	*aeavol*	Lerman, Livnat & Mendenhall	2007, WP
75	Change in # analysts	*chnanalyst*	Scherbina	2007, WP
76	Asset growth	*agr*	Cooper, Gulen & Schill	2008, JF
77	Change in shares outstanding	*chcsho*	Pontiff & Woodgate	2008, JF
78	Industry-adjusted change in profit margin	*chpmia*	Soliman	2008, TAR
79	Industry-adjusted change in asset turnover	*chatoia*	Soliman	2008, TAR
80	3-day return around earnings announcement	*ear*	Kishore, Brandt, Santa-Clara & Venkatachalam	2008, WP
81	Revenue surprise	*rsup*	Kama	2009, JBFA
82	Cash flow volatility	*stdcf*	Huang	2009, JEF
83	Debt capacity-to-firm tangibility	*tang*	Hahn & Lee	2009, JF
84	Sin stock	*sin*	Hong & Kacperczyk	2009, JFE
85	Employee growth rate	*hire*	Bazdresch, Belo & Lin	2009, WP
86	Cash productivity	*cashpr*	Chandrashekar & Rao	2009, WP
87	ROA	*roaq*	Balakrishnan, Bartov & Faurel	2010, JAE
88	CAPEX and inventory	*invest*	Chen & Zhang	2010, JF
89	Real estate holdings	*realestate*	Tuzel	2010, RFS
90	Absolute accruals	*absacc*	Bandyopadhyay, Huang & Wirjanto	2010, WP
91	Accrual volatility	*stdacc*	Bandyopadhyay, Huang & Wirjanto	2010, WP
92	Change in tax expense	*chtx*	Thomas & Zhang	2010, WP
93	Maximum daily return in prior month	*maxret*	Bali, Cakici & Whitelaw	2011, JFE
94	Percent accruals	*pctacc*	Hafzalla, Lundholm & Van Winkle	2011, TAR
95	Cash holdings	*cash*	Palazzo	2012, JFE
96	Gross profitability	*gma*	Novy-Marx	2012, WP
97	Organizational capital	*orgcap*	Eisfeldt & Papanikolaou	2013, JF
98	Secured debt-to-total debt	*secured*	Valta	2013, WP
99	Secured debt indicator	*securedind*	Valta	2013, WP
100	Convertible debt indicator	*convind*	Valta	2013, WP

TABLE 2

Definitions of the return predictive signals (RPS) used in the study, sorted by acronym

RPS #	Acronym	RPS definition (annual figures are for most recent fiscal year prior to signal date)
90	*absacc*	Absolute value of *acc*.
36	*acc*	Annual income before extraordinary items (ib) minus operating cash flows (oancf) divided by avg total assets (at). If oancf is missing then oancf is set to ib minus change in act minus change in che minus change in lct plus change in dlc plus change in {txp less dp}, where each item is set to zero if missing.
74	*aeavol*	Avg daily trading volume (vol) for 3 days centered on earnings announcement date minus avg daily volume in month ending 2 weeks before earnings announcement divided by 1 month avg daily volume; earnings announcement day is from Compustat quarterly (rdq).
63	*age*	Number of years since first year of Compustat coverage.
76	*agr*	Annual % change in total assets (at).
21	*baspread*	Monthly avg of daily bid-ask spread divided by avg of daily bid-ask spread.
1	*beta*	Beta estimated from 3 years of weekly firm and EW market returns ending month t-1 (with at least 52 weeks of returns available).
2	*betasq*	Beta squared.
8	*bm*	Book value of equity (ceq) divided by end of fiscal year end market cap.
29	*bm_ia*	Industry-adjusted book-to-market.
95	*cash*	Cash + cash equivalents (che) divided by avg total assets (at).
20	*cashdebt*	Earnings before depreciation and extraordinary items (ib+dp) divided by avg total liabilities (lt).
86	*cashpr*	Fiscal year end market cap plus long term debt (dltt) minus total assets (at) divided by cash and equivalents (che).
58	*cfp*	Operating cash flows (oancf) divided by FYE market cap.
28	*cfp_ia*	Industry-adjusted *cfp*.
79	*chatoia*	2-digit sic fiscal year mean-adjusted change in sales (sale) divided by avg total assets (at) .
77	*chcsho*	Annual % change in shares outstanding (csho).
31	*chempia*	Industry-adjusted change in number of employees (emp).
7	*chfeps*	Mean analyst forecast of annual EPS in month prior to fiscal period end date from IBES summary file minus same mean forecast for prior fiscal period.
52	*chinv*	Change in inventory (invt) divided by avg total assets (at).
72	*chmom*	Cumulative return for months t-6 to t-1 minus cumulative return for months t-12 to t-7.
75	*chnanalyst*	Change in *nanalyst* from month t-3 to month t.
78	*chpmia*	2-digit sic fiscal year mean-adjusted change in income before extraordinary items (ib) divided by sales (sale).
92	*chtx*	% change in total taxes (txtq) from quarter t-4 to t.
56	*cinvest*	Change over one quarter in net PPE (ppentq) divided by sales (saleq) scaled by avg of this variable for prior 3 quarters. If saleq = 0 then scale by 0.01.
100	*convind*	Indicator = 1 if the firm has convertible debt obligations.
12	*currat*	Current assets (act) divided by current liabilities (lct).
25	*depr*	Depreciation expense (dp) divided by gross PPE (ppegt).
51	*disp*	Standard deviation of analyst annual earnings forecasts in month prior to fiscal period end date divided by the absolute value of the mean forecast. If meanest=0 then scalar set to 1. Forecast data from IBES summary files.
33	*divi*	Indicator = 1 if company pays dividends but did not in prior year.
34	*divo*	Indicator = 1 if company does not pay dividends but did in prior year.
46	*dolvol*	Natural log of trading volume times price per share from month t-2.
5	*dy*	Total dividends (dvt) divided by market cap at fiscal year end.
80	*ear*	Sum of daily returns in three days around earnings announcement (date from Compustat quarterly file (rdq)).
61	*egr*	Annual % change in book value of equity (ceq).
3	*ep*	Annual income before extraordinary items (ib) divided by market cap at end of prior fiscal year.
10	*fgr5yr*	Most recently available analyst forecasted 5-year growth in annual EPS.
96	*gma*	Sales (sale) minus cost of goods sold (cogs) divided by lagged total assets (at).
70	*grcapex*	% change in capital expenditures (capx) from year t-2 to year t.
54	*grltnoa*	Growth in long term net operating assets.
69	*herf*	2 digit sic-fiscal year sales concentration [sum of squared % of sales in industry for each company].
85	*hire*	% change in number of employees (emp).
53	*idiovol*	Standard deviation of residuals of weekly returns on weekly EW market returns for 3 years prior to month end.
62	*ill*	Avg of daily values of absolute return divided by dollar volume.
44	*indmom*	EW avg industry 12-month returns.
88	*invest*	Annual change in gross property, plant, and equipment (ppegt) + annual change in inventories (invt) all divided by lagged total assets (at).
32	*IPO*	Indicator = 1 if first year available on CRSP monthly file.
11	*lev*	Total liabilities (lt) divided by fiscal year end market cap.
60	*lgr*	Annual % change in total liabilities (lt).
93	*maxret*	Max daily return in calendar month t-1.
24	*mom12m*	11-month cumulative returns ending month t-2.
22	*mom1m*	Return in month t-1.

TABLE 2 (continued)

RPS #	Acronym	RPS definition (annual figures are for most recent fiscal year prior to signal date)
9	*mom36m*	24-month cumulative return ending month t-13.
23	*mom6m*	5-month cumulative return ending month t-2.
64	*ms*	Sum of 9 indicator variables that form fundamental performance measure M-score.
4	*mve*	Natural log of market cap at month-end immediately prior to signal date (prc*shrout).
27	*mve_ia*	Industry-adjusted fiscal year-end market cap.
50	*nanalyst*	Number of analyst forecasts from most recently available IBES summary files in month prior to month of portfolio formation, number of analysts set to zero of not covered in IBES summary file.
43	*nincr*	Number of consecutive quarters (up to eight) with an increase in earnings (ibq) over same quarter in the prior year.
97	*orgcap*	Capitalized SG&A expenses.
40	*pchcapx_ia*	2 digit sic fiscal year mean adjusted % change in capital expenditures (capx).
13	*pchcurrat*	% change in *currat*.
26	*pchdepr*	% change in *depr*.
41	*pchgm_pchsale*	Annual % change in gross margin (sale minus cogs) minus % change in sales (sale).
15	*pchquick*	% change in *quick*.
38	*pchsale_pchinvt*	Annual % change in sales (sale) minus annual % change in inventory (invt).
39	*pchsale_pchrect*	Annual % change in sales (sale) minus annual % change in receivables (rect).
42	*pchsale_pchxsga*	Annual % change in sales (sale) minus annual % change in SG&A (xsga).
19	*pchsaleinv*	% change in *saleinv*.
94	*pctacc*	Annual income before extraordinary items (ib) minus operating cash flows (oancf) divided by the abs{ib}; unless ib=0 then ib=0.01. If oancf is missing then oancf is set to ib minus change in act minus change in che minus change in lct plus change in dlc plus change in {txp less dp}, where each item is set to zero if missing.
65	*pricedelay*	Proportion of variation in weekly returns for 36 months ending in month t explained by 4 lags of weekly market returns incremental to contemporaneous market return.
45	*ps*	Sum of 9 indicator variables that form fundamental financial health F-score.
14	*quick*	Current assets (act) minus inventory (invt), divided by current liabilities (lct).
55	*rd*	Indicator = 1 if R&D expense as a percentage of total assets has year-to-year increase of more than 5%.
67	*rd_mve*	R&D expense (xrd) divided by end of fiscal year market cap.
66	*rd_sale*	R&D expense divided by sales (xrd/sale).
89	*realestate*	Buildings and capitalized leases divided by gross PP&E.
68	*retvol*	Standard deviation of daily returns in month t-1.
87	*roaq*	Income before extraordinary items (ibq) divided by one quarter lagged total assets (atq).
59	*roavol*	Standard deviation for 16 quarters of income before extraordinary items (ibq) divided by avg total assets (atq).
73	*roic*	Annual earnings before interest and taxes (ebit) minus non-operating income (nopi), divided by non-cash enterprise value (ceq+lt-che).
81	*rsup*	Sales from quarter t minus sales from quarter t-4 (saleq) divided by fiscal quarter end market cap (cshoq * prccq).
16	*salecash*	Annual sales (sale) divided by cash and cash equivalents (che).
18	*saleinv*	Annual sales (sale) divided by total inventory (invt).
17	*salerec*	Annual sales (sale) divided by accounts receivable (rect).
98	*secured*	Total liability scaled secured debt.
99	*securedind*	Indicator = 1 if company has secured debt obligations.
49	*sfe*	Analysts' mean earnings forecast of current year annual earnings from IBES summary files scaled by price per share at end of most recent fiscal quarter.
30	*sgr*	Annual % change in sales (sale).
84	*sin*	Indicator = 1 if a company's primary industry classification is in smoke, tobacco, beer, alcohol or gaming.
35	*sp*	Annual revenue (sale) divided by fiscal year end market cap.
47	*std_dolvol*	Monthly standard deviation of daily dollar trading volume.
48	*std_turn*	Monthly standard deviation of daily share turnover.
91	*stdacc*	Standard deviation for 16 quarters of accruals scaled by sales. If saleq=0 then scale by 0.01, accruals is defined as change in non-cash current assets minus change in current liabilities minus change in debt in current liabilities (change in actq minus change in cheq minus change in lctq plus change in dlcq). If item is missing it is set to zero. Change is for 1 quarter change.
82	*stdcf*	Standard deviation for prior 16 quarters of cash flows divided by sales (saleq); if saleq equal to zero then scale by 0.01; cash flows defined as ibq minus accruals as defined in *stdacc*.
6	*sue*	Unexpected quarterly earnings divided by market cap at end of most recent fiscal quarter. Unexpected earnings is IBES actual earnings minus median forecasted earnings if available; else unexpected earnings is the seasonally differenced quarterly earnings before extraordinary items from Compustat quarterly file.
83	*tang*	[Cash holdings + (0.715 × receivables) + (0.547 × inventory (invt)) + (0.535 × PPE (ppegt))] divided by total assets (at).
57	*tb*	Taxable income, set as current tax expense divided by maximum federal tax rate, divided by income before extraordinary items (ib).
37	*turn*	Avg monthly trading volume for the three months t-3 to t-1 scaled by number of shares outstanding at end of month t-1.
71	*zerotrade*	Turnover-weighted number of zero trading days for most recent 1 month.

TABLE 3

Description of CRSP and Compustat data items that were either deleted or set to zero, and RPS missing values that were set to the real-time monthly mean value for that RPS

Panel A: Firm-month observations deleted due to no valid market cap or book value of equity

	# obs./month
Missing market cap or book equity	46

Panel B: Firm-month observations deleted due to extreme or impossible CRSP stock returns

Return outlier condition	# obs.
Monthly stock return > 10,000%	1
Monthly stock return < -100%	52

Panel C: Frequency of missing Compustat or I/B/E/S data items set to zero

Compustat data item	Compustat annual file identifier	% of obs. reset to zero
R&D expense	*xrd*	54.6%
Capitalized leases--PP&E	*fatl*	52.3%
Buildings--PP&E	*fatb*	47.4%
Debt mortgages and other secured	*dm*	18.9%
Number of employees	*emp*	12.2%
Intangible assets	*intan*	9.7%
Convertible debt	*dcvt*	8.5%
Other current liabilities	*lco*	7.7%
Other current assets	*aco*	7.7%
Depreciation	*dp*	3.9%
Total receivables	*rect*	2.4%
Total inventory	*invt*	2.1%
Accounts payable	*ap*	1.0%
Total dividends	*dvt*	0.6%
Other assets	*ao*	0.3%
Cash and cash equivalents	*che*	0.3%
Non-operating income	*nopi*	0.2%
Other liabilities	*lo*	0.1%
Total assets	*at*	0.0%
I/B/E/S data item (only for years starting 1989)	I/B/E/S identifier	% of obs. reset to zero
Number of analysts issuing earnings forecast	*nanalyst*	35.6%

TABLE 3 (continued)

Panel D: Number and percentage of firm-month observations set to real-time monthly mean for that RPS

RPS #	RPS Acronym	# firm-month obs. post-Compustat and I/B/E/S resets	% of firm-month obs. reset to RPS month mean	RPS #	RPS Acronym	# firm-month obs. post-Compustat and I/B/E/S resets	% of firm-month obs. reset to RPS month mean
10	*fgr5yr*	750,195	62%	45	*ps*	1,849,990	7%
51	*disp*	802,803	60%	52	*chinv*	1,849,990	7%
49	*sfe*	959,759	52%	55	*rd*	1,849,990	7%
7	*chfeps*	977,712	51%	60	*lgr*	1,843,840	7%
19	*pchsaleinv*	1,437,861	28%	61	*egr*	1,849,793	7%
59	*roavol*	1,425,620	28%	76	*agr*	1,849,957	7%
82	*stdcf*	1,425,620	28%	77	*chcsho*	1,849,007	7%
91	*stdacc*	1,425,620	28%	85	*hire*	1,844,528	7%
97	*orgcap*	1,453,762	27%	96	*gma*	1,845,300	7%
38	*pchsale_pchinvt*	1,461,189	26%	46	*dolvol*	1,897,150	5%
75	*chnanalyst*	1,493,809	25%	73	*roic*	1,896,790	5%
9	*mom36m*	1,512,004	24%	17	*salerec*	1,915,569	4%
50	*nanalyst*	1,515,638	24%	23	*mom6m*	1,910,139	4%
42	*pchsale_pchxsga*	1,530,539	23%	47	*std_dolvol*	1,918,606	3%
18	*saleinv*	1,561,123	21%	48	*std_turn*	1,924,420	3%
70	*grcapex*	1,650,117	17%	62	*ill*	1,922,298	3%
6	*sue*	1,694,392	15%	71	*zerotrade*	1,922,328	3%
12	*currat*	1,693,059	15%	1	*beta*	1,949,992	2%
14	*quick*	1,693,059	15%	2	*betasq*	1,949,992	2%
79	*chatoia*	1,695,660	15%	25	*depr*	1,955,524	2%
81	*rsup*	1,694,412	15%	37	*turn*	1,946,489	2%
92	*chtx*	1,694,224	15%	53	*idiovol*	1,949,992	2%
43	*nincr*	1,718,825	14%	65	*pricedelay*	1,949,961	2%
56	*cinvest*	1,702,206	14%	66	*rd_sale*	1,955,550	2%
64	*ms*	1,718,825	14%	16	*salecash*	1,967,987	1%
74	*aeavol*	1,706,462	14%	83	*tang*	1,969,631	1%
80	*ear*	1,717,417	14%	86	*cashpr*	1,964,487	1%
87	*roaq*	1,717,053	14%	3	*ep*	1,987,340	0%
95	*cash*	1,718,746	14%	4	*mve*	1,987,340	0%
36	*acc*	1,724,752	13%	5	*dy*	1,987,340	0%
90	*absacc*	1,724,752	13%	8	*bm*	1,987,340	0%
94	*pctacc*	1,724,740	13%	11	*lev*	1,981,906	0%
28	*cfp_ia*	1,755,669	12%	20	*cashdebt*	1,980,259	0%
57	*tb*	1,755,372	12%	21	*baspread*	1,987,294	0%
58	*cfp*	1,755,669	12%	22	*mom1m*	1,987,340	0%
26	*pchdepr*	1,760,216	11%	32	*IPO*	1,987,340	0%
39	*pchsale_pchrect*	1,769,186	11%	35	*sp*	1,981,691	0%
40	*pchcapx_ia*	1,795,780	10%	44	*indmom*	1,987,214	0%
78	*chpmia*	1,815,857	9%	27	*mve_ia*	1,987,340	0%
24	*mom12m*	1,820,468	8%	29	*bm_ia*	1,987,340	0%
30	*sgr*	1,820,506	8%	63	*age*	1,987,340	0%
41	*pchgm_pchsale*	1,820,295	8%	67	*rd_mve*	1,987,340	0%
54	*grltnoa*	1,831,854	8%	68	*retvol*	1,987,278	0%
72	*chmom*	1,820,468	8%	69	*herf*	1,987,328	0%
88	*invest*	1,829,166	8%	84	*sin*	1,987,340	0%
13	*pchcurrat*	1,849,990	7%	89	*realestate*	1,987,340	0%
15	*pchquick*	1,849,990	7%	93	*maxret*	1,987,308	0%
31	*chempia*	1,844,528	7%	98	*secured*	1,987,340	0%
33	*divi*	1,849,990	7%	99	*securedind*	1,987,340	0%
34	*divo*	1,849,990	7%	100	*convind*	1,987,340	0%

TABLE 4

Descriptive statistics on the degree of cross-correlation between the 100 RPS used in this study. Each firm's scaled decile ranked RPS are recalculated monthly by ranking every RPS into deciles (0-9) and dividing by 9. Before ranking, certain missing data items are set to zero and all RPS with missing values are reset to that month's mean RPS value (see Table 3).

Panel A: Distribution of variance inflation factors (VIFs) from pooled time-series cross-sectional regressions of 1-month ahead stock returns on RPS

	Before removing RPS with VIF > 6	After removing RPS with VIF > 6
# RPS	100	91
Min.	1.0	1.0
Median	2.1	1.8
Mean	4.4	2.2
max.	61.7	5.2
# VIFs > 6	15	0

RPS removed in reducing the set of 100 RPS to 91 RPS

- *betasq*
- *quick*
- *pchquick*
- *sp*
- *ill*
- *rd_sale*
- *stdacc*
- *maxret*
- *secured*

Panel B: Distribution of absolute cross-correlations in scaled decile ranked RPS (before and after removal of RPS with extreme VIFs) and in RPS hedge returns

Cross-correlations in:	Min.	1st pctile	25th pctile	Median	Mean	75th pctile	99th pctile	Max.
SDR RPS (pooled cross-section time-series)	0.00	0.00	0.01	0.04	0.08	0.11	0.53	0.99
SDR RPS (by month)	0.00	0.00	0.02	0.05	0.09	0.12	0.55	1.00
SDR RPS (pooled, after extreme VIF removal)	0.00	0.00	0.01	0.03	0.08	0.10	0.50	0.75

Panel C: Absolute cross-correlations in scaled decile ranked RPS after removal of extreme VIF RPS

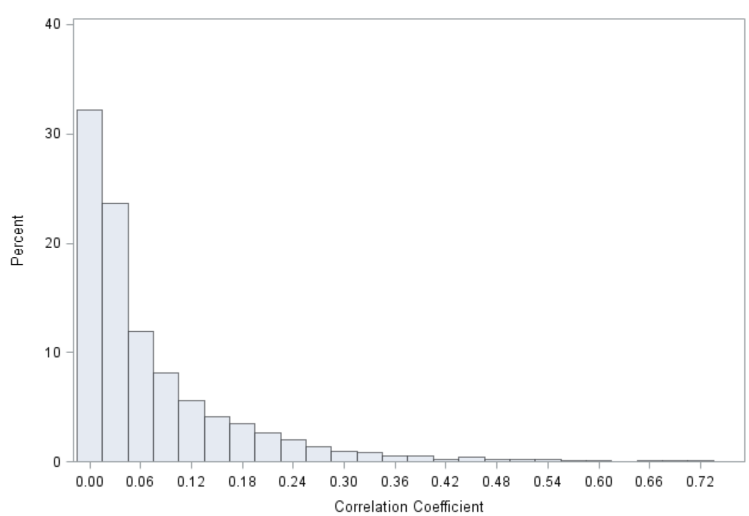


TABLE 5

Mean annualized long/short hedge returns (MALSRets) and associated t-statistics implied by slope coefficients estimated from Fama-MacBeth type regressions of 1-month ahead firm returns over 1980-2012 on monthly scaled decile ranked RPS. Each month the RPS *mve*, *bm*, *mom12m*, *roic*, *agr* are recalculated by ranking the RPS into deciles (0-9) and dividing by 9. Before ranking, certain missing data items are set to zero and missing RPS values are reset to that month's mean RPS value (see Table 3). Estimated monthly MALSRets are annualized by multiplying by 12. t-statistics use Newey-West adjustments of 12 lags. Large-Cap are the largest 1,000 companies by market cap; Mid-Cap are the next largest 2,000 companies; Small-Cap are all remaining firms.

Panel A: Fama-French (1992) RPS + Jegadeesh (1990) RPS

		All firms		Large-Cap		Mid-Cap		Small-Cap	
RPS	Pred. sign	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.
mve	-	-4.1%	-0.9	-1.7%	-1.0	2.6%	1.4	-23.0%	-5.2
bm	+	13.2%	3.5	3.1%	0.9	12.5%	2.9	13.8%	3.4
mom12m	+	5.8%	5.8	6.0%	3.8	5.6%	5.3	5.4%	3.9
Mean # obs. per regression		5,015		996		1,997		2,016	
Mean adjusted R^2		2.0%		2.0%		2.0%		1.0%	

Panel B: Fama-French (2013) RPS

		All firms		Large-Cap		Mid-Cap		Small-Cap	
RPS	Pred. sign	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.
mve	-	-6.4%	-1.8	-1.8%	-1.2	0.9%	0.5	-23.0%	-5.9
bm	+	11.4%	3.0	5.4%	1.5	11.0%	2.6	10.0%	2.7
roic	+	12.0%	3.8	7.5%	2.9	13.4%	4.2	11.8%	3.0
agr	-	-13.8%	-7.2	-4.2%	-2.2	-11.0%	-6.3	-17.4%	-5.7
Mean # obs. per regression		5,014		995		1,996		2,015	
Mean adjusted R^2		2.0%		3.0%		2.0%		1.0%	

Panel C: Fama-French (2013) RPS + Jegadeesh (1990) RPS

		All firms		Large-Cap		Mid-Cap		Small-Cap	
RPS	Pred. sign	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.
mve	-	-6.4%	-1.8	-1.9%	-1.2	0.9%	0.6	-23.0%	-5.9
bm	+	11.4%	3.0	5.3%	1.5	11.1%	2.7	10.1%	2.7
roic	+	12.1%	3.8	7.5%	2.9	13.4%	4.3	11.9%	3.1
agr	-	-13.9%	-7.2	-4.2%	-2.3	-11.0%	-6.3	-17.6%	-5.8
mom12m	+	5.1%	6.3	5.1%	4.0	4.7%	5.4	4.5%	3.8
Mean # obs. per regression		5,013		994		1,995		2,014	
Mean adjusted R^2		2.0%		3.0%		2.0%		1.0%	

TABLE 6

Mean annualized long/short hedge returns (MALSRets) and associated t-statistics from unidimensional (N = 1) and multidimensional (N = 91) Fama-MacBeth regressions RET = a + b_1RPS_1 + ... $b_N.RPS_N$ + e on 1-month ahead ahead firm-specific returns, 1980-2012. Each firm's scaled decile ranked RPS are recalculated monthly by ranking each RPS into deciles (0-9) and dividing by 9. Before ranking, certain missing data items are set to zero and missing RPS values are reset to that month's mean RPS (see Table 3). Estimated MALSRets are annualized by multiplying by 12. t-statistics use Newey-West adjustments of 12 lags. Predicted coefficient signs are from the RPS literature. Multidimensional regressions use the 91 RPS described in Table 4 after removing those RPS with the largest VIFs. MALSRets with an absolute t-statistic ≥ 3.0 are color-highlighted in each column. Large-Cap are the largest 1,000 companies by market cap; Mid-Cap are the next largest 2,000 companies; Small-Cap are all remaining firms.

Panel A: Mean annualized long/short hedge returns (MALSRets) and associated t-statistics from scaled decile ranked RPS Fama-Macbeth regressions

			All firms				Multimensional (by firm size)					
			Unidimensional		Multidimensional		Large-Cap		Mid-Cap		Small-Cap	
	# abs{t-stat} ≥ 1.96		48		46		20		29		34	
	# abs{t-stat} ≥ 3.0		35		24		6		20		21	
	Mean # obs. per regression		5,032		4,930		910		1,911		1,931	
	Mean adjusted R^2		0.4%		6.0%		17.0%		9.0%		4.0%	
	RPS	Pred. sign	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.
1	*beta*	+	-3.8%	-0.7	1.7%	0.7	-0.6%	-0.3	2.5%	1.0	0.2%	0.1
2	*betasq*	+	-4.0%	-0.8								
3	*ep*	+	6.5%	1.2	6.2%	4.3	4.4%	3.1	5.1%	3.4	13.7%	5.7
4	*mve*	-	-6.5%	-1.6	-9.0%	-1.7	-4.4%	-1.7	-1.9%	-0.9	-31.8%	-7.0
5	*dy*	+	0.9%	0.2	-1.9%	-1.7	-1.5%	-1.3	-4.6%	-3.4	-3.9%	-1.6
6	*sue*	+	20.3%	15.8	11.2%	14.2	-0.7%	-0.7	6.9%	5.4	20.0%	14.2
7	*chfeps*	+	7.3%	6.0	1.8%	2.3	1.7%	1.7	4.8%	4.5	4.1%	3.1
8	*bm*	+	15.1%	4.5	8.2%	4.4	5.5%	3.0	4.4%	2.0	7.8%	2.0
9	*mom36m*	-	8.6%	5.2	0.9%	2.3	0.8%	1.6	0.1%	0.3	1.5%	1.3
10	*fgr5yr*	-	-0.9%	-0.2	-5.1%	-4.8	0.9%	0.6	-3.7%	-3.7	-2.9%	-1.5
11	*lev*	+	6.5%	1.6	5.6%	2.3	8.6%	2.3	14.7%	4.7	-4.2%	-1.3
12	*currat*	+	1.3%	0.8	0.8%	0.6	-2.9%	-2.6	2.4%	2.2	1.3%	0.6
13	*pchcurrat*	+	-1.0%	-0.7	-0.2%	-0.3	-0.5%	-0.7	0.6%	0.8	-1.9%	-1.5
14	*quick*	+	1.5%	0.7								
15	*pchquick*	+	-0.4%	-0.3								
16	*salecash*	+	1.9%	0.6	-3.6%	-2.9	2.1%	1.4	2.5%	1.7	-8.4%	-3.5
17	*salerec*	+	4.4%	2.2	2.2%	1.5	1.3%	0.9	1.9%	1.1	0.3%	0.1
18	*saleinv*	+	3.0%	2.2	5.4%	5.4	0.4%	0.4	3.5%	3.7	8.1%	4.8
19	*pchsaleinv*	+	1.2%	0.9	2.3%	1.8	0.8%	0.6	1.4%	0.9	3.8%	1.7
20	*cashdebt*	+	3.7%	1.0	-0.5%	-0.3	3.7%	1.5	3.5%	1.6	-4.0%	-1.5
21	*baspread*	-	-2.8%	-0.5	3.2%	1.5	3.5%	2.6	4.5%	2.2	7.0%	2.9
22	*mom1m*	-	4.2%	4.5	-1.4%	-3.6	0.2%	0.2	-0.7%	-1.0	-2.6%	-2.5
23	*mom6m*	+	8.6%	5.4	-0.1%	-0.1	-0.1%	-0.1	0.4%	0.3	-0.5%	-0.2
24	*mom12m*	+	9.8%	6.1	0.7%	0.7	-0.5%	-0.4	0.4%	0.4	0.8%	0.4
25	*depr*	+	6.0%	1.7	3.0%	2.5	1.8%	1.5	3.7%	2.9	3.9%	2.6
26	*pchdepr*	-	1.5%	1.1	-1.5%	-2.0	0.6%	0.7	-0.2%	-0.2	-4.3%	-3.0
27	*mve_ia*	-	-0.7%	-0.4	4.8%	3.9	2.4%	1.2	1.7%	1.1	2.0%	1.3
28	*cfp_ia*	+	-1.6%	-1.0	-0.5%	-0.5	0.1%	0.1	-1.7%	-1.6	1.5%	0.9
29	*bm_ia*	+	7.3%	3.3	-2.4%	-1.9	-0.8%	-0.8	-1.9%	-1.6	-2.5%	-0.8
30	*sgr*	-	-8.8%	-5.2	0.1%	0.1	-0.9%	-0.8	0.9%	0.7	-1.2%	-0.6

TABLE 6 (continued)

			All firms				Multimensional (by firm size)					
			Unidimensional		Multidimensional		Large-Cap		Mid-Cap		Small-Cap	
	RPS	Pred. sign	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.
31	*chempia*	-	-5.3%	-3.4	-0.8%	-0.6	1.9%	1.5	0.0%	0.0	-2.5%	-1.0
32	*IPO*	-	-9.0%	-4.3	-3.2%	-2.1	-0.8%	-0.5	-2.7%	-1.6	-3.1%	-1.4
33	*divi*	+	-2.4%	-1.8	-1.5%	-1.3	-2.0%	-0.8	0.8%	0.7	-2.1%	-1.1
34	*divo*	-	-0.2%	-0.2	0.0%	0.0	1.2%	0.6	-1.8%	-1.4	2.5%	1.2
35	*sp*	+	14.0%	4.0								
36	*acc*	-	-8.1%	-4.1	-2.6%	-2.2	-3.2%	-2.0	-3.8%	-2.9	-1.2%	-0.5
37	*turn*	+	21.9%	9.1	23.4%	10.0	1.8%	0.7	17.1%	7.8	32.7%	9.4
38	*pchsale_pchinvt*	+	4.5%	5.6	-1.8%	-1.5	0.3%	0.2	-0.6%	-0.5	-3.0%	-1.3
39	*pchsale_pchrect*	-	2.4%	2.5	0.1%	0.2	0.0%	-0.1	-1.4%	-2.1	2.2%	1.9
40	*pchcapx_ia*	-	-5.1%	-3.5	-1.9%	-2.3	-0.5%	-0.6	-1.9%	-1.9	-2.7%	-2.2
41	*pchgm_pchsale*	+	3.8%	3.3	1.5%	2.3	0.3%	0.4	0.8%	1.4	2.8%	1.7
42	*pchsale_pchxsga*	+	-0.1%	-0.1	0.5%	0.8	-0.7%	-1.1	-0.3%	-0.4	1.8%	1.3
43	*nincr*	+	12.7%	8.7	1.4%	2.3	0.6%	0.8	1.7%	1.9	-2.8%	-1.4
44	*indmom*	+	25.8%	7.3	7.2%	6.3	4.4%	4.0	6.9%	5.0	7.4%	4.7
45	*ps*	+	5.6%	2.5	-1.4%	-1.7	0.9%	1.1	-0.8%	-0.7	-1.7%	-1.0
46	*dolvol*	-	1.0%	1.5	-9.1%	-9.3	-0.5%	-0.5	-7.3%	-6.9	-14.1%	-6.3
47	*std_dolvol*	-	4.5%	1.9	-6.4%	-3.4	-4.3%	-2.4	-0.4%	-0.4	-3.3%	-1.3
48	*std_turn*	-	4.0%	1.2	8.8%	3.5	7.4%	2.6	3.7%	1.9	3.3%	1.2
49	*sfe*	+	-8.1%	-1.7	-14.5%	-12.6	-18.0%	-10.1	-18.5%	-9.7	-8.8%	-6.2
50	*nanalyst*	-	-4.5%	-1.4	2.4%	1.0	-3.6%	-1.8	-1.8%	-1.1	15.0%	4.4
51	*disp*	-	-0.1%	0.0	-3.0%	-2.4	1.8%	1.3	0.6%	0.5	-6.2%	-2.5
52	*chinv*	-	-9.0%	-5.7	-1.0%	-1.1	-0.9%	-0.6	0.0%	0.0	-2.5%	-1.2
53	*idiovol*	-	-2.4%	-0.4	3.6%	1.5	-1.9%	-1.3	-2.5%	-1.4	5.0%	1.8
54	*grltnoa*	-	-10.8%	-5.5	-0.3%	-0.4	-3.1%	-2.6	-2.1%	-1.6	-0.7%	-0.4
55	*rd*	+	6.3%	2.3	1.1%	2.0	-0.2%	-0.2	0.8%	1.1	1.5%	1.3
56	*cinvest*	-	2.8%	2.9	-0.7%	-1.2	-0.9%	-1.6	-0.8%	-1.0	-0.1%	-0.1
57	*tb*	+	4.3%	1.7	0.8%	1.0	0.6%	0.8	1.5%	2.0	1.8%	1.3
58	*cfp*	+	1.7%	0.6	-1.0%	-1.1	1.6%	1.4	0.8%	0.7	-2.3%	-1.7
59	*roavol*	+	-1.1%	-0.2	0.5%	0.5	-0.5%	-0.5	1.6%	1.4	1.2%	0.7
60	*lgr*	-	-11.7%	-8.6	-2.0%	-1.8	-0.3%	-0.2	-2.2%	-1.9	-2.7%	-1.3
61	*egr*	-	-7.7%	-2.9	0.4%	0.5	-2.3%	-2.2	-1.5%	-1.4	2.1%	1.1
62	*ill*	+	2.8%	0.9								
63	*age*	+	6.5%	2.2	0.2%	0.2	-2.2%	-1.9	0.5%	0.4	1.4%	0.5
64	*ms*	+	1.8%	0.8	-1.0%	-1.4	-0.1%	-0.2	1.2%	1.4	-5.2%	-3.4
65	*pricedelay*	+	2.0%	1.7	1.3%	2.4	0.0%	0.0	0.7%	1.3	-0.6%	-0.4
66	*rd_sale*	+	5.0%	0.9								
67	*rd_mve*	+	9.0%	1.7	10.2%	4.3	3.8%	1.7	6.3%	2.7	14.3%	5.2
68	*retvol*	-	-5.7%	-1.0	-11.6%	-6.6	-7.2%	-4.4	-16.8%	-10.5	-8.8%	-2.6
69	*herf*	-	-2.4%	-1.1	-3.7%	-2.4	-0.2%	-0.1	-2.1%	-1.2	-5.3%	-3.2
70	*grcapex*	-	-8.9%	-5.6	-1.5%	-2.3	-0.9%	-1.0	-1.8%	-2.3	0.3%	0.2
71	*zerotrade*	+	3.2%	1.0	11.0%	4.4	3.7%	2.0	-0.6%	-0.3	-1.1%	-0.4
72	*chmom*	-	0.6%	1.2	0.5%	0.5	-0.3%	-0.3	0.7%	0.6	0.7%	0.4
73	*roic*	+	4.7%	1.1	3.3%	2.6	4.2%	2.8	1.4%	0.9	2.8%	1.3
74	*aeavol*	+	8.0%	7.0	3.0%	5.7	0.1%	0.2	2.8%	3.7	4.6%	4.9
75	*chnanalyst*	-	-3.1%	-1.6	0.8%	1.1	0.6%	0.6	0.1%	0.1	-0.4%	-0.3
76	*agr*	-	-15.8%	-5.9	-7.4%	-4.8	0.3%	0.2	-5.7%	-4.1	-8.3%	-2.8
77	*chcsho*	-	-12.3%	-5.7	-1.8%	-2.8	-0.7%	-0.9	-0.1%	-0.2	-2.8%	-2.3
78	*chpmia*	+	0.0%	0.0	0.7%	0.7	-1.1%	-1.2	0.9%	0.8	0.6%	0.4
79	*chatoia*	+	4.0%	5.6	1.1%	1.8	2.0%	2.7	0.1%	0.2	2.6%	2.1
80	*ear*	+	16.5%	16.6	9.3%	13.7	0.5%	0.8	7.7%	9.1	16.4%	11.2

TABLE 6 (continued)

			All firms				Multimensional (by firm size)					
			Unidimensional		Multidimensional		Large-Cap		Mid-Cap		Small-Cap	
	RPS	Pred. sign	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.	MALSRet	t-stat.
81	*rsup*	+	7.9%	3.8	6.7%	7.5	1.8%	2.4	5.6%	6.0	8.5%	6.5
82	*stdcf*	-	-7.8%	-2.7	-3.3%	-3.2	1.7%	1.8	0.9%	0.7	-14.0%	-6.2
83	*tang*	+	4.2%	1.4	1.3%	1.0	0.0%	0.0	1.0%	0.8	2.5%	1.3
84	*sin*	+	4.6%	1.9	5.3%	2.7	2.1%	1.1	0.4%	0.1	18.4%	2.5
85	*hire*	-	-9.6%	-5.4	0.5%	0.4	-0.6%	-0.5	1.6%	1.2	1.1%	0.5
86	*cashpr*	-	-9.4%	-2.9	-0.3%	-0.3	2.1%	1.4	-1.4%	-1.1	-1.0%	-0.4
87	*roaq*	+	13.2%	3.3	9.6%	7.1	4.1%	2.6	10.0%	6.5	8.0%	4.3
88	*invest*	-	-12.3%	-5.9	-0.4%	-0.4	1.7%	1.1	0.2%	0.2	-0.2%	-0.1
89	*realestate*	+	2.1%	1.4	-0.6%	-0.7	0.7%	0.7	0.7%	0.7	0.9%	0.6
90	*absacc*	-	-0.5%	-0.2	-2.4%	-2.9	0.1%	0.1	-3.2%	-4.0	-1.7%	-1.2
91	*stdacc*	-	-8.1%	-2.9								
92	*chtx*	+	12.4%	9.6	3.0%	3.8	2.5%	2.3	3.4%	3.4	4.8%	3.3
93	*maxret*	-	-8.8%	-1.8								
94	*pctacc*	-	-6.5%	-4.3	-2.6%	-1.9	-0.5%	-0.3	-1.8%	-1.4	-4.8%	-2.0
95	*cash*	+	5.1%	1.3	2.8%	2.7	6.1%	5.0	7.3%	4.8	0.4%	0.2
96	*gma*	+	4.3%	2.5	0.5%	0.3	-1.7%	-0.8	1.9%	1.2	1.1%	0.3
97	*orgcap*	+	8.7%	3.0	3.3%	2.2	2.3%	1.6	1.4%	1.2	-0.7%	-0.3
98	*secured*	+	1.6%	0.5								
99	*securedind*	+	0.6%	0.3	1.0%	0.6	0.7%	0.6	1.5%	0.9	2.4%	0.9
100	*convind*	+	-5.0%	-4.2	-2.8%	-4.3	-1.1%	-2.0	-2.3%	-2.5	-3.7%	-2.5

Panel B: Attenuation of unidimensionally measured RPS MALSRets and t-statistics when the RPS are measured multidimensionally. The tables below report the results of regressing multidimensionally measured RPS MALSRets and t-statistics onto their unidimensionally measured equivalents, where the latter are reported in panel A for all firms but are calculated but not reported for large-cap, mid-cap and small-cap firms.

MALSRets	All firms	Large-Cap	Mid-Cap	Small-Cap
Intercept	0.2%	0.1%	0.2%	-0.3%
t-stat (null = 0)	(0.4)	(0.3)	(0.5)	(-0.5)
Slope	0.41	0.39	0.36	0.51
t-stat (null = 0)	(7.8)	(5.7)	(7.2)	(8.9)
t-stat [null = 1]	[11.0]	[8.8]	[12.7]	[8.4]
Adj. R-sq.	40%	26%	36%	47%

t-stat(MALSRet)	All firms	Large-Cap	Mid-Cap	Small-Cap
Intercept	0.0	0.0	0.0	-0.1
t-stat (null = 0)	(0.0)	(0.1)	(0.0)	(-0.3)
Slope	0.58	0.57	0.49	0.50
t-stat (null = 0)	(7.7)	(5.5)	(6.3)	(9.3)
t-stat [null = 1]	[5.7]	[4.2]	[6.6]	[9.3]
Adj. R-sq.	40%	24%	30%	49%

TABLE 7

Mean estimated coefficients and associated t-statistics from unidimensional (N = 1) and multidimensional (N = 91) Fama-MacBeth regressions RET = a + b_1RPS$_1$ + ... b_N.RPS$_N$ + e on 1-month ahead ahead firm-specific returns for 1980-2012. After certain missing data items are set to zero and missing RPS values are reset to that month's mean RPS value (see Table 3), each month RPS are winsorized and standardized to a cross-sectional mean of zero and a standard deviation of one. Predicted coefficient signs are from the RPS literature. Estimated coefficients are shown X100 and then X12, making them the annualized percent returns accruing to a one standard deviation increase in the individual RPS. Multidimensional regressions use the 91 RPS described in Table 4 after removing those RPS with the largest VIFs. t-statistics use Newey-West adjustments of 12 lags, and estimated coefficients with an absolute t-statistic ≥ 3.0 are color-highlighted in each column. Large-Cap are the largest 1,000 companies by market cap; Mid-Cap are the next largest 2,000 companies; Small-Cap are all remaining firms.

Panel A: Mean estimated coefficients and associated t-statistics from standardized RPS Fama-MacBeth regressions

			Unidimensional		Multidimensional		Large-Cap		Mid-Cap		Small-Cap	
	# abs{t-stat} ≥ 1.96		51		43		14		33		27	
	# abs{t-stat} ≥ 3.0		34		28		5		20		19	
	Mean # obs. per regression		5,032		4,930		911		1,911		1,931	
	Mean adjusted R^2		0.3%		7.0%		18.0%		10.0%		5.0%	
	RPS	Pred. sign	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
1	*beta*	+	-1.5%	-0.8	0.5%	0.5	0.3%	0.2	0.8%	0.8	0.7%	0.7
2	*betasq*	+	-1.3%	-0.8								
3	*ep*	+	0.7%	0.4	3.3%	5.4	3.8%	4.5	2.6%	4.5	4.9%	6.6
4	*mve*	-	-3.0%	-2.2	-9.8%	-5.8	-2.7%	-1.8	-6.8%	-4.0	-41.5%	-9.7
5	*dy*	+	0.6%	1.0	-0.1%	-0.5	1.6%	1.3	-2.0%	-2.3	0.0%	0.0
6	*sue*	+	6.6%	17.9	3.9%	14.6	-0.2%	-0.4	2.8%	6.6	4.9%	14.1
7	*chfeps*	+	2.5%	6.2	1.0%	3.3	0.2%	0.7	1.4%	4.2	2.0%	4.1
8	*bm*	+	4.3%	4.9	1.6%	3.1	1.9%	2.4	0.7%	1.0	0.4%	0.5
9	*mom36m*	-	2.4%	7.0	0.3%	2.2	0.3%	1.2	0.2%	0.8	0.3%	0.9
10	*fgr5yr*	-	-0.5%	-0.4	-0.3%	-0.8	0.7%	0.7	-0.4%	-1.1	1.1%	1.5
11	*lev*	-	0.2%	0.2	-0.5%	-1.0	0.5%	0.3	0.2%	0.3	-0.7%	-1.2
12	*currat*	+	0.0%	0.1	-0.4%	-1.5	-1.5%	-2.4	-0.8%	-2.3	0.2%	0.5
13	*pchcurrat*	+	-0.3%	-0.8	-0.3%	-1.4	-0.5%	-1.6	0.2%	0.6	-0.6%	-1.5
14	*quick*	+	-0.1%	-0.1								
15	*pchquick*	+	-0.1%	-0.2								
16	*salecash*	+	0.2%	1.1	0.1%	0.5	2.0%	0.8	-0.5%	-1.2	0.1%	0.3
17	*salerec*	+	0.2%	0.6	0.0%	-0.1	1.4%	1.4	0.6%	1.7	-0.4%	-0.7
18	*saleinv*	+	0.1%	0.9	0.1%	0.9	0.5%	0.5	0.9%	1.5	3.0%	2.5
19	*pchsaleinv*	+	-0.2%	-0.8	-0.2%	-0.9	-7.2%	-1.1	1.6%	0.4	-0.2%	-0.3
20	*cashdebt*	+	0.6%	0.7	-0.1%	-0.5	-1.9%	-1.1	0.6%	0.9	-0.6%	-1.4
21	*baspread*	-	1.5%	0.8	3.6%	3.2	2.4%	0.6	-1.1%	-0.5	1.2%	1.3
22	*mom1m*	-	1.2%	3.8	0.1%	0.7	-0.1%	-0.2	0.3%	1.2	-0.4%	-1.2
23	*mom6m*	+	2.4%	5.6	1.1%	2.8	-0.6%	-0.7	1.8%	2.6	1.2%	1.3
24	*mom12m*	+	2.6%	6.2	-0.9%	-2.4	0.4%	0.5	-1.1%	-2.3	-1.2%	-1.4
25	*depr*	+	0.5%	1.1	0.3%	1.1	-5.3%	-1.3	1.1%	0.6	-0.1%	-0.3
26	*pchdepr*	-	0.3%	0.5	-0.5%	-1.8	0.6%	1.6	0.1%	0.4	-1.1%	-2.6
27	*mve_ia*	-	-0.3%	-0.5	1.5%	3.1	0.2%	0.5	-0.3%	-0.5	-1.0%	-1.1
28	*cfp_ia*	+	-0.5%	-1.1	-0.1%	-0.4	-0.1%	-0.3	-0.4%	-1.0	0.4%	0.7
29	*bm_ia*	+	1.3%	2.0	-0.4%	-0.8	-0.3%	-0.6	0.0%	-0.1	-0.2%	-0.3
30	*sgr*	-	-3.1%	-6.1	-0.6%	-1.7	-0.5%	-0.8	-0.2%	-0.4	-0.8%	-1.0

TABLE 7 (continued)

			Unidimensional		Multidimensional		Large-Cap		Mid-Cap		Small-Cap	
	RPS	Pred. sign	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
31	*chempia*	-	-2.1%	-4.6	0.1%	0.1	0.6%	1.1	0.5%	0.9	-0.8%	-0.9
32	*IPO*	-	-9.0%	-4.3	-4.3%	-2.8	-1.0%	-0.7	-3.9%	-2.3	-4.9%	-2.2
33	*divi*	+	-2.4%	-1.8	-1.3%	-1.3	-1.3%	-0.5	-0.2%	-0.1	-2.0%	-1.2
34	*divo*	-	-0.2%	-0.2	0.6%	0.6	3.0%	1.4	-0.8%	-0.7	2.6%	1.3
35	*sp*	+	2.0%	2.7								
36	*acc*	-	-2.4%	-3.3	-1.2%	-3.4	-1.3%	-1.7	-1.4%	-3.2	-1.1%	-2.0
37	*turn*	+	1.7%	5.7	0.6%	1.9	1.2%	0.3	1.9%	3.1	0.1%	0.4
38	*pchsale_pchinvt*	+	1.2%	3.8	0.1%	0.5	0.3%	1.1	-0.2%	-0.7	-0.1%	-0.1
39	*pchsale_pchrect*	-	0.6%	2.1	0.1%	0.4	-0.4%	-1.2	-0.4%	-1.6	0.6%	1.5
40	*pchcapx_ia*	-	-1.1%	-2.2	-0.3%	-0.8	-0.5%	-1.5	0.0%	0.0	-0.2%	-0.4
41	*pchgm_pchsale*	+	1.4%	4.1	0.7%	3.3	0.4%	1.4	0.5%	2.3	0.8%	1.9
42	*pchsale_pchxsga*	+	0.0%	-0.1	0.3%	1.4	0.1%	0.4	-0.1%	-0.5	0.8%	1.9
43	*nincr*	+	2.9%	5.5	1.0%	5.0	0.2%	1.4	0.7%	3.0	0.5%	0.6
44	*indmom*	+	7.4%	7.3	2.3%	7.7	1.5%	4.9	2.2%	6.4	2.4%	6.0
45	*ps*	+	1.9%	2.7	0.1%	0.3	0.5%	1.8	0.3%	1.1	-0.2%	-0.4
46	*dolvol*	-	0.3%	1.6	0.0%	0.1	-0.1%	-0.7	-0.1%	-0.5	0.1%	0.3
47	*std_dolvol*	-	1.4%	2.0	-0.7%	-1.4	-1.4%	-1.7	0.0%	0.0	-1.2%	-1.5
48	*std_turn*	-	-1.2%	-2.0	-0.8%	-1.7	-0.5%	-0.6	0.8%	1.5	-0.5%	-0.7
49	*sfe*	+	-1.6%	-1.1	-3.3%	-10.2	-5.1%	-6.5	-3.4%	-6.3	-2.7%	-5.4
50	*nanalyst*	-	-1.0%	-1.0	3.9%	4.1	-0.7%	-1.6	0.7%	0.7	31.3%	4.6
51	*disp*	-	-1.1%	-3.1	-0.7%	-3.4	2.5%	1.5	-0.6%	-1.6	-4.6%	-1.8
52	*chinv*	-	-2.9%	-5.7	-0.7%	-2.3	-0.4%	-0.7	-0.6%	-1.6	-1.2%	-1.9
53	*idiovol*	-	-0.9%	-0.5	-1.9%	-2.9	-2.0%	-1.4	-1.9%	-2.4	-2.3%	-2.7
54	*grltnoa*	-	-3.9%	-6.6	-0.8%	-2.3	-1.4%	-2.8	-1.2%	-2.5	-0.8%	-1.3
55	*rd*	+	6.3%	2.3	2.0%	2.8	0.3%	0.4	0.7%	0.9	4.1%	3.0
56	*cinvest*	-	0.7%	2.6	-0.2%	-1.4	-0.4%	-1.9	-0.1%	-0.6	-0.2%	-0.7
57	*tb*	+	1.1%	2.0	0.7%	3.2	0.2%	0.5	0.6%	3.0	1.2%	3.2
58	*cfp*	+	-0.2%	-0.2	-0.5%	-1.6	-0.3%	-0.6	-0.7%	-1.7	-0.4%	-1.0
59	*roavol*	+	-0.3%	-0.6	0.2%	1.0	33.2%	1.7	-3.6%	-1.6	1.3%	0.1
60	*lgr*	-	-3.8%	-9.0	-0.8%	-3.3	0.3%	0.6	-0.3%	-0.9	-1.4%	-3.1
61	*egr*	-	-2.5%	-3.3	-0.1%	-0.5	-0.6%	-1.4	-0.7%	-2.3	0.4%	0.9
62	*ill*	+	3.7%	4.6								
63	*age*	+	1.9%	1.9	0.9%	2.4	-0.6%	-1.7	-0.1%	-0.3	1.2%	1.4
64	*ms*	+	0.5%	0.7	0.1%	0.3	0.2%	0.6	0.5%	1.5	-0.7%	-1.6
65	*pricedelay*	+	0.5%	1.4	0.0%	0.1	0.2%	0.4	-0.1%	-0.3	-0.1%	-0.4
66	*rd_sale*	+	-0.2%	-0.8								
67	*rd_mve*	+	3.4%	2.8	2.5%	5.1	4.6%	2.4	4.1%	3.8	2.2%	4.6
68	*retvol*	-	-2.1%	-1.3	-3.4%	-3.0	-7.3%	-3.6	-11.7%	-7.8	-2.9%	-2.4
69	*herf*	-	-0.7%	-1.4	-0.6%	-1.9	0.1%	0.4	-0.1%	-0.2	-0.5%	-1.2
70	*grcapex*	-	-2.7%	-6.7	-0.7%	-3.4	-0.2%	-0.6	-0.7%	-3.4	-0.3%	-0.9
71	*zerotrade*	+	1.0%	1.5	-2.8%	-5.4	-0.8%	-0.2	-2.6%	-4.1	-4.1%	-6.4
72	*chmom*	-	0.2%	1.1	-0.7%	-2.5	0.3%	0.6	-1.0%	-2.0	-0.8%	-1.1
73	*roic*	+	1.2%	0.8	0.8%	1.4	1.2%	1.5	0.3%	0.5	0.7%	1.0
74	*aeavol*	+	3.4%	9.7	1.6%	7.0	0.3%	0.8	1.0%	3.3	2.5%	8.2
75	*chnanalyst*	-	-1.0%	-1.6	-0.1%	-0.4	0.2%	0.9	0.0%	-0.2	-0.6%	-0.9
76	*agr*	-	-2.7%	-6.4	-0.7%	-2.5	-1.6%	-0.5	-3.0%	-1.8	-0.5%	-0.5
77	*chcsho*	-	-3.7%	-7.1	-1.0%	-4.9	-0.1%	-0.6	-0.2%	-0.8	-1.7%	-3.6
78	*chpmia*	+	-0.2%	-0.4	0.1%	0.3	-0.4%	-1.4	0.3%	0.8	0.2%	0.3
79	*chatoia*	+	1.2%	5.1	0.7%	2.5	0.7%	2.0	0.5%	2.1	0.8%	1.6
80	*ear*	+	6.2%	19.7	4.1%	16.1	0.7%	2.0	3.4%	9.6	5.5%	10.6

TABLE 7 (continued)

	RPS	Pred. sign	Unidimensional Coef.	Unidimensional t-stat.	Multidimensional Coef.	Multidimensional t-stat.	Large-Cap Coef.	Large-Cap t-stat.	Mid-Cap Coef.	Mid-Cap t-stat.	Small-Cap Coef.	Small-Cap t-stat.
81	*rsup*	+	2.3%	3.2	1.9%	5.2	0.8%	1.8	1.9%	4.3	2.2%	5.6
82	*stdcf*	-	-0.1%	-0.3	0.1%	0.3	5.9%	1.8	-0.8%	-0.4	-24.7%	-2.0
83	*tang*	+	1.3%	1.3	0.0%	0.0	-1.0%	-2.3	0.4%	1.0	0.5%	0.9
84	*sin*	+	4.6%	1.9	5.4%	2.7	2.1%	1.1	1.9%	0.6	15.1%	2.3
85	*hire*	-	-3.4%	-6.3	-0.2%	-0.3	-0.2%	-0.3	-0.2%	-0.4	0.3%	0.4
86	*cashpr*	-	-2.5%	-2.9	-0.5%	-1.6	0.0%	0.0	-1.1%	-4.2	0.4%	0.8
87	*roaq*	+	3.9%	2.8	1.7%	4.5	1.1%	1.6	2.1%	5.1	0.8%	1.4
88	*invest*	-	-4.3%	-6.5	-0.7%	-1.6	0.8%	1.6	-0.9%	-1.7	-0.4%	-0.5
89	*realestate*	+	0.4%	1.1	-0.3%	-1.0	0.4%	1.4	0.2%	0.6	0.0%	0.1
90	*absacc*	-	-0.8%	-0.9	-0.7%	-2.2	1.6%	1.7	-0.4%	-1.2	-0.6%	-1.4
91	*stdacc*	-	-0.1%	-0.3								
92	*chtx*	+	4.1%	9.5	1.8%	7.2	0.9%	2.5	1.5%	4.7	2.4%	5.8
93	*maxret*	-	-3.4%	-2.5								
94	*pctacc*	-	-2.1%	-5.5	-0.7%	-2.8	-0.2%	-0.3	-0.6%	-2.2	-1.0%	-2.4
95	*cash*	+	1.5%	1.1	2.2%	3.9	3.2%	3.8	1.8%	2.7	2.8%	4.5
96	*gma*	+	1.1%	2.1	0.6%	1.0	0.4%	0.6	0.9%	2.0	0.5%	0.6
97	*orgcap*	+	2.4%	2.9	0.2%	0.5	0.2%	0.3	0.1%	0.2	-0.6%	-0.9
98	*secured*	+	-0.4%	-1.6								
99	*securedind*	+	0.6%	0.3	0.8%	0.5	1.0%	0.8	2.0%	1.4	1.0%	0.4
100	*convind*	+	-5.0%	-4.2	-2.5%	-3.7	-1.1%	-2.1	-1.6%	-1.7	-4.9%	-3.3

Panel B: Pearson correlations between the t-statistics on unidimensioned RPS and multidimensioned RPS reported in panel A of Tables 6 and 7.

	All firms		Multimensional (by firm size)		
	Unidimensional	Multidimensional	Large-Cap	Mid-Cap	Small-Cap
Corr (t-stat_SDR, t-stat_norm)	0.97	0.77	0.81	0.79	0.81

TABLE 8

Comparison of multidimensioned results that use scaled decile ranked RPS with results where RPS are winsorized and standardized to a mean of zero and standard deviation of 1. Coefficient estimates in panel A are X100 and are annualized long/short hedge returns. Coefficient estimates in panel B are X100 and then X12, making them the annualized returns to a one standard deviation increase in the individual RPS. Absolute t-statistics ≥ 3.0 are color-highlighted by firm-size group.

Panel A: Scaled decile ranked RPS

			All firms				Multimensional (by firm size)					
			Unidimensional		Multidimensional		Large-Cap		Mid-Cap		Small-Cap	
# abs{t-stat} ≥ 1.96			48		46		20		29		34	
# abs{t-stat} ≥ 3.0			35		24		6		20		21	
Mean # obs. per regression			5,032		4,930		910		1,911		1,931	
Mean adjusted R^2			0.4%		6.0%		17.0%		9.0%		4.0%	
10 largest multidimensional t-stats.							10 largest multidimensional t-stats.					
#	RPS	Pred. sign	MALSRet	t-stat.	MALSRet	t-stat.	RPS	t-stat.	RPS	t-stat.	RPS	t-stat.
1	*sue*	+	20.3%	15.8	11.2%	14.2	*sfe*	-10.1	*retvol*	-10.5	*sue*	14.2
2	*ear*	+	16.5%	16.6	9.3%	13.7	*cash*	5.0	*sfe*	-9.7	*ear*	11.2
3	*sfe*	+	-8.1%	-1.7	-14.5%	-12.6	*retvol*	-4.4	*ear*	9.1	*turn*	9.4
4	*turn*	+	21.9%	9.1	23.4%	10.0	*indmom*	4.0	*turn*	7.8	*mve*	-7.0
5	*dolvol*	-	1.0%	1.5	-9.1%	-9.3	*ep*	3.1	*dolvol*	-6.9	*rsup*	6.5
6	*rsup*	+	7.9%	3.8	6.7%	7.5	*bm*	3.0	*roaq*	6.5	*dolvol*	-6.3
7	*roaq*	+	13.2%	3.3	9.6%	7.1			*rsup*	6.0	*sfe*	-6.2
8	*retvol*	-	-5.7%	-1.0	-11.6%	-6.6			*sue*	5.4	*stdcf*	-6.2
9	*indmom*	+	25.8%	7.3	7.2%	6.3			*indmom*	5.0	*ep*	5.7
10	*aeavol*	+	8.0%	7.0	3.0%	5.7			*cash*	4.8	*rd_mve*	5.2
15	*bm*	+	15.1%	4.5	8.2%	4.4	*bm*	3.0	*bm*	2.0	*bm*	2.0
52	*mve*	-	-6.5%	-1.6	-9.0%	-1.7	*mve*	-1.7	*mve*	-0.9	*mve*	-7.0
70	*mom12m*	+	9.8%	6.1	0.7%	0.7	*mom12m*	-0.4	*mom12m*	0.4	*mom12m*	0.4

Panel B: Normalized RPS

			All firms				Multimensional (by firm size)					
			Unidimensional		Multidimensional		Large-Cap		Mid-Cap		Small-Cap	
# abs{t-stat} ≥ 1.96			51		43		14		33		27	
# abs{t-stat} ≥ 3.0			34		28		5		20		19	
Mean # obs. per regression			5,032		4,930		911		1,911		1,931	
Mean adjusted R^2			0.3%		7.0%		18.0%		10.0%		5.0%	
10 largest multidimensional t-stats.							10 largest multidimensional t-stats.					
#	RPS	Pred. sign	Coef.	t-stat.	Coef.	t-stat.	RPS	t-stat.	RPS	t-stat.	RPS	t-stat.
1	*ear*	+	6.2%	19.7	4.1%	16.1	*sfe*	-6.5	*ear*	9.6	*sue*	14.1
2	*sue*	+	6.6%	17.9	3.9%	14.6	*indmom*	4.9	*retvol*	-7.8	*ear*	10.6
3	*sfe*	+	-1.6%	-1.1	-3.3%	-10.2	*ep*	4.5	*sue*	6.6	*mve*	-9.7
4	*indmom*	+	7.4%	7.3	2.3%	7.7	*cash*	3.8	*indmom*	6.4	*aeavol*	8.2
5	*chtx*	+	4.1%	9.5	1.8%	7.2	*retvol*	-3.6	*sfe*	-6.3	*ep*	6.6
6	*aeavol*	+	3.4%	9.7	1.6%	7.0			*roaq*	5.1	*zerotrade*	-6.4
7	*mve*	-	-3.0%	-2.2	-9.8%	-5.8			*chtx*	4.7	*indmom*	6.0
8	*ep*	+	0.7%	0.4	3.3%	5.4			*ep*	4.5	*chtx*	5.8
9	*zerotrade*	+	1.0%	1.5	-2.8%	-5.4			*rsup*	4.3	*rsup*	5.6
10	*rsup*	+	2.3%	3.2	1.9%	5.2			*chfeps*	4.2	*sfe*	-5.4
27	*bm*	+	4.3%	4.9	1.6%	3.1	*bm*	2.4	*bm*	1.0	*bm*	0.5
7	*mve*	-	-3.0%	-2.2	-9.8%	-5.8	*mve*	-1.8	*mve*	-4.0	*mve*	-9.7
39	*mom12m*	+	2.6%	6.2	-0.9%	-2.4	*mom12m*	0.5	*mom12m*	-2.3	*mom12m*	-1.4
53	*roic*	+	1.2%	0.8	0.8%	1.4	*roic*	1.5	*roic*	0.5	*roic*	1.0
14	*agr*	-	-2.7%	-6.4	-0.7%	-2.5	*agr*	-0.5	*agr*	-1.8	*agr*	-0.5

TABLE 9

The sets of RPS selected via panel LASSO regressions, using mean-adjusted monthly returns as the dependent variable. Missing values are set equal to zero. RPS variables are ranked into deciles (0-9) and divided by 9. Ranking is performed for sample used in regressions; i.e. ranking for all firms and separately for large, mid-size, and small firms. Large-Cap are the largest 1,000 companies by market cap; Mid-Cap are the next largest 2,000 companies; Small-Cap are all remaining firms.

	All firms	Large-Cap	Mid-Cap	Small-Cap
1	*sue*	*ep*	*ep*	*mve*
2	*bm*	*mom36m*	*sue*	*sue*
3	*mom36m*	*mom1m*	*chfeps*	*bm*
4	*mom12m*	*mom12m*	*bm*	*quick*
5	*sp*	*sp*	*mom6m*	*saleinv*
6	*acc*	*indmom*	*sp*	*turn*
7	*turn*	*sfe*	*acc*	*indmom*
8	*nincr*	*grltnoa*	*turn*	*dolvol*
9	*indmom*	*roic*	*indmom*	*std_turn*
10	*dolvol*	*agr*	*sfe*	*nanalyst*
11	*sfe*	*chcsho*	*grltnoa*	*rd_mve*
12	*rd_mve*	*chtx*	*agr*	*aeavol*
13	*aeavol*	*maxret*	*ear*	*agr*
14	*agr*		*cashpr*	*chcsho*
15	*chcsho*		*roaq*	*ear*
16	*ear*		*invest*	*tang*
17	*roaq*		*chtx*	*stdacc*
18	*invest*		*maxret*	*maxret*
19	*maxret*			

TABLE 10

Tests of factor portfolio returns. Every month, for each of the 100 RPS listed in Table 1, firms are ranked into deciles. Then, for each RPS decile and each month, an equally-weighted RPS decile portfolio return is created using firms' returns in the subsequent month, yielding a time series of monthly portfolio returns for each of the 1,000 RPS decile combinations. For each RPS decile, a time series regression of that RPS decile's monthly portfolio returns on the factor returns pertinent to one of four alternative factor models is then estimated: [1] the equally-weighted market EW; [2] EW and the long/short hedge portfolio factor returns to market cap, book-to-market and 12 month momentum; [3] EW and the factor returns to market cap, book-to-market, profitability and asset growth; [4] the model that selects the five factor returns from the set of 100 RPS-based factor returns with the highest time series adjusted R^2. Then for each RPS the mean absolute value of the regression intercepts and the mean adjusted R^2 across the 10 deciles are calculated. Panel A reports descriptive statistics on these 100 mean absolute intercepts and 100 adjusted R^2 (one per RPS), while Panel B reports the frequency with which the factors chosen by model [4] overlap with those of models [1] – [3].

Panel A: Performance of factor return models [1] – [4]

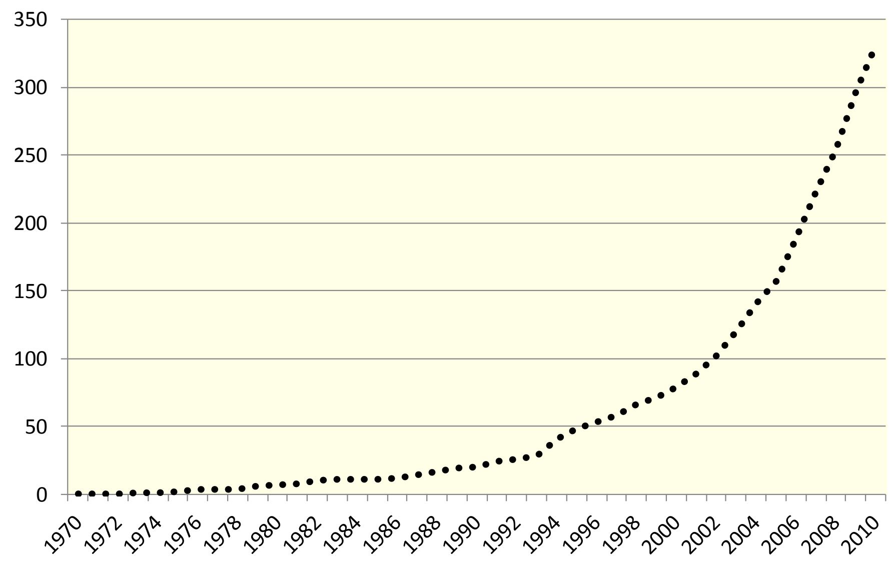
Factor Model		Statistic	Min.	Q1	Median	Mean	Q3	Max.
[1]	Equally-weighted market EW	mean_absint	0.06%	0.18%	0.25%	0.27%	0.34%	0.51%
		mean_adjR^2	75.7%	90.1%	92.6%	91.7%	94.6%	98.8%
[2]	EW and the long/short hedge portfolio factor returns to firm size, book-to-market and 12 month momentum	mean_absint	0.05%	0.11%	0.16%	0.19%	0.23%	0.91%
		mean_adjR^2	78.9%	93.9%	95.4%	94.5%	96.2%	98.8%
[3]	EW and the factor returns to market cap, book-to-market, profitability and asset growth	mean_absint	0.02%	0.11%	0.18%	0.20%	0.26%	0.81%
		mean_adjR^2	80.5%	94.9%	95.9%	95.2%	96.8%	98.9%
[4]	The model that selects the five factor returns from the set of 100 RPS-based factor returns with the highest time series adjusted R^2	mean_absint	0.01%	0.08%	0.10%	0.12%	0.14%	0.45%
		mean_adjR^2	84.1%	96.7%	97.7%	97.0%	98.1%	99.7%

Panel B: Frequency with which factors chosen by model [4] overlap with those of models [1] – [3]

Factor Model or Factor Return	Frequency
Model [1]	51%
Model [2]	0%
Model [3]	0%
Firm size *mve*	17%
Book-to-market *bm*	4%
12-month momentum *mom12m*	2%
Profitability *roic*	5%
Asset growth *agr*	6%

FIGURE 1

Cumulative number of firm-specific return predictive signals (RPS) publicly reported in Green, Hand and Zhang (2013) as having been discovered by accounting, finance and other business academics, 1970-2010.



The number of RPS each year is the sum of the accounting-based, finance-based and other-based RPS reported in Figure 1 of Green, Hand and Zhang (2013).

FIGURE 2

Principal component factor analysis (PCA) of theset of 100 scaled decile ranked RPS, and of the monthly RPS hedge returns. Only factors with an eigenvalue > 1.0 are shown. The x-axis is the number of RPS factors and the y-axis is the variance explained by each factor

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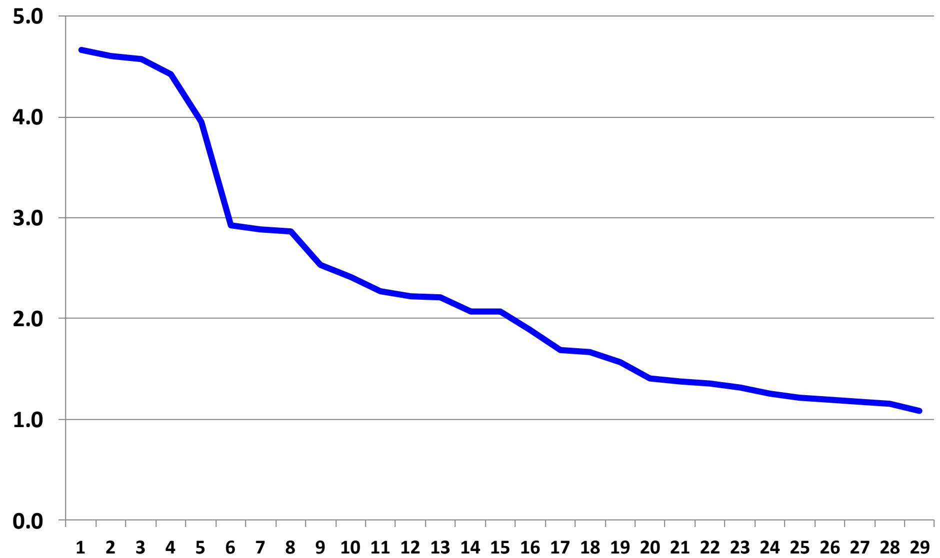
Panel A: Variance explained by PCA-derived factors in the set of 100 scaled decile ranked RPS



Panel B: Variance explained by PCA-derived factors of the monthly long/short biggest/smallest decile RPS hedge returns

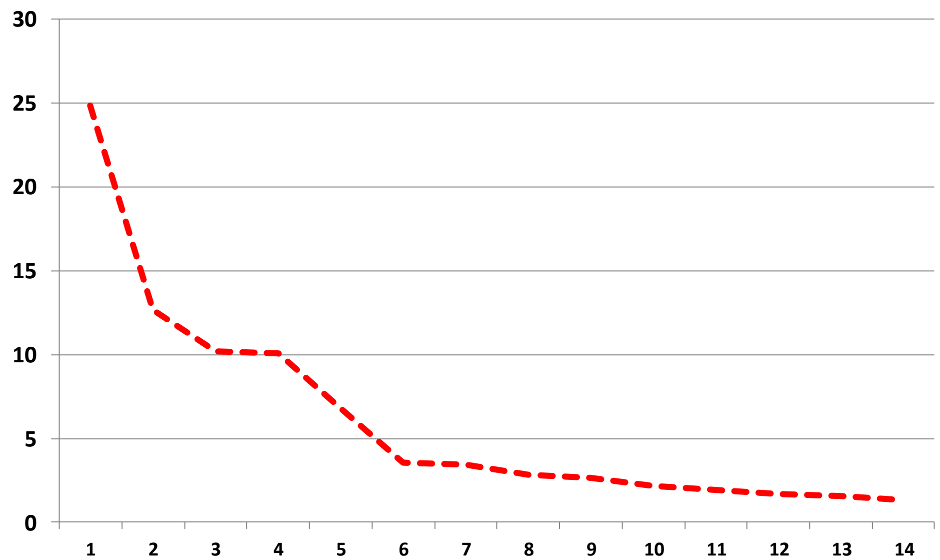


FIGURE 3

Out-of-sample hedge portfolio returns to alternative sets of RPS. Analysis is limited to large-cap and mid-cap firms only; small-cap firms are excluded. Hedge portfolio returns are defined as the sum of wt x rret each month, where wt = 2 x [pret]/[abs(pret]. pret is the predicted mean-adjusted return based on estimating rolling 10-year regressions of mean-adjusted returns on the relevant set of RPS, and then applying the estimated coefficients to the RPS in place at the end of the 10-year window to estimate the next month's predicted return. rret is the realized return in the month immediately after the end of the 10-year estimation window.

Panel A: Statistics on monthly out-of-sample 2X-levered hedge portfolio returns, and their associated annualized Sharpe ratios

	Statistics on monthly out of sample hedge returns							
Multidimensioned set of RPS	t-stat.	Min.	10th pctile	50th pctile	Mean	90th pctile	Max.	Annualized Sharpe
Carhart (1997): *mve, bm, mom12m*	4.8	-7.0%	-2.3%	0.4%	0.8%	4.2%	9.0%	0.99
Fama & French (2013): *mve, bm, roic, agr, mom12m*	5.2	-9.2%	-2.7%	0.7%	1.1%	4.9%	15.5%	1.08
ALL: All RPS (n = 91)	12.4	-11.8%	0.0%	2.1%	2.7%	6.3%	37.1%	2.58

Panel B: Ln(1+cumulative out-of-sample 2X gross levered hedge portfolio returns) for various sets of multidimensioned RPS

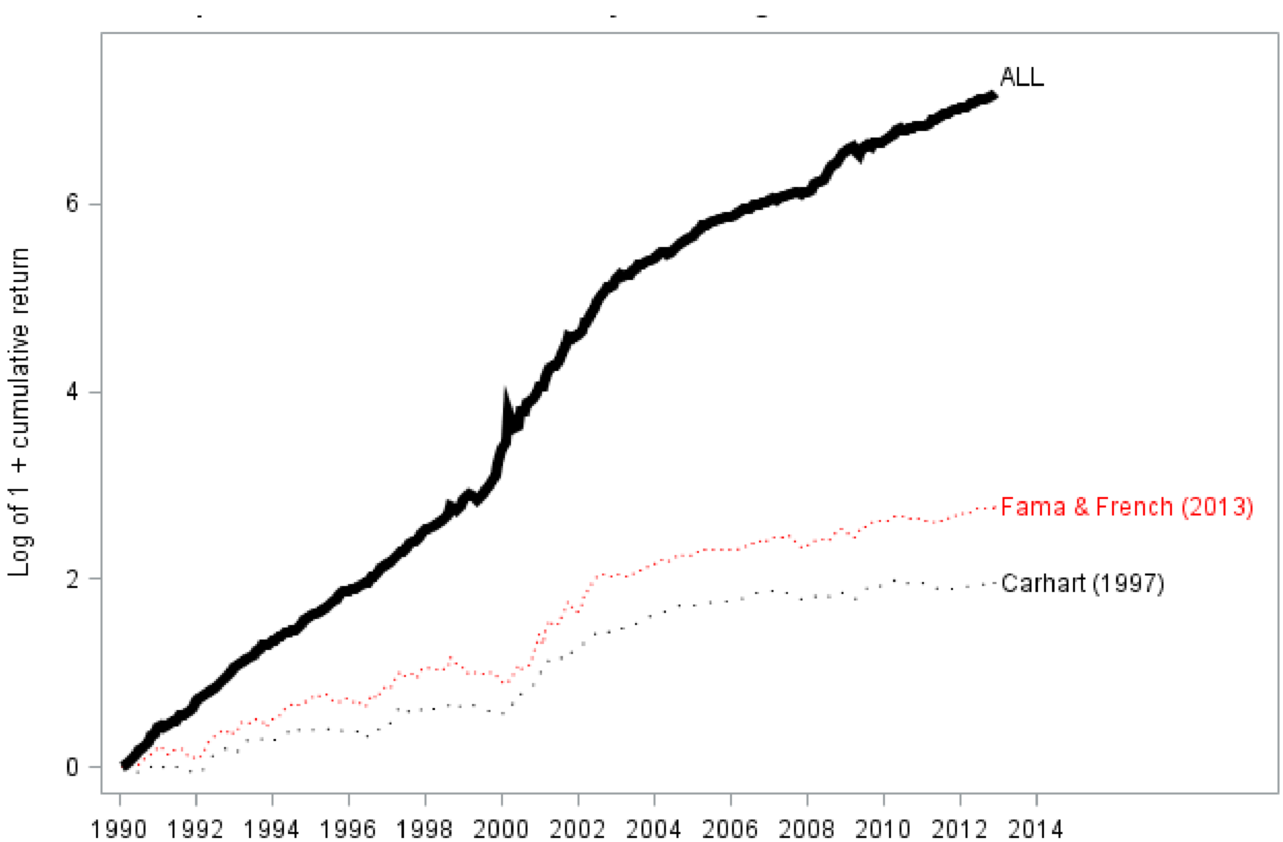


FIGURE 4

Comparison of the out-of-sample hedge portfolio returns to the ALL RPS reported in Figure 4 with the distilled 10 RPS model. The RPS in the distilled 10 RPS model are: asset growth *agr*, book-to-market *bm*, dollar trading volume *dolvol*, quarterly earnings announcement returns *ear*, 12-month industry-adjusted returns *indmom*, 36 month momentum *mom36m*, quarterly return on assets *roaq*, forecasted annual earnings *sfe*, unexpected quarterly earnings *sue*, and share turnover *turn*. Exact RPS definitions are in Table 2. The RPS in the distilled model are those that yield the largest adjusted R^2 in a pooled time-series cross-sectional regression of 1-month ahead mean-adjusted U.S. stock returns, Jan. 1980-Dec. 2012. Analysis is limited to large-cap and mid-cap firms only. Hedge portfolio returns are constructed per Figure 3.

Panel A: Statistics on monthly out-of-sample 2X-levered hedge portfolio returns, and their associated annualized Sharpe ratios

	Statistics on monthly out of sample hedge returns							
Multidimensioned set of RPS	t-stat.	Min.	10th pctile	50th pctile	Mean	90th pctile	Max.	Annualized Sharpe
ALL: All RPS (n = 91)	12.4	-11.8%	0.0%	2.1%	2.7%	6.3%	37.1%	2.58
TEN: Distilled 10 RPS model	14.1	-4.1%	0.2%	2.2%	2.5%	5.0%	32.0%	2.94

Panel B: Ln(1+cumulative out-of-sample 2X gross levered hedge portfolio returns) for various sets of multidimensioned RPS