The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns

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Abstract

We take up Cochrane's (2011) challenge that researchers identify the firm characteristics that provide independent information about average U.S. monthly stock returns. For 94 firm characteristics that we simultaneously include in Fama-MacBeth regressions that seek to avoid overweighting microcaps and adjust for data snooping bias, for the full period 1980-2014 we estimate that 8-12 characteristics are significant independent determinants of average returns. However, we also observe striking variation over calendar time, with return predictability falling suddenly and to such a degree in 2003 that since then only 1-2 characteristics have been significant in the non-microcap cross-section of stocks, and the mean raw and factor-orthogonalized hedge returns to the set of 94 characteristics have been insignificantly different from zero. We discuss potential reasons for why such a large change in the return generating process has taken place, and its implications for empirical models of stock returns.

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1. Introduction

In his Presidential address to the American Finance Association, Cochrane (2011, p.1060) challenges researchers to identify the firm characteristics that provide independent information about average U.S. stock returns. Cochrane issues his challenge because of the 'veritable zoo' of hundreds of characteristics that have been presented as being statistically significant predictors of the cross-section of returns in the vast anomalies literature since 1970 (Green, Hand and Zhang, 2013; Hou, Xue and Zhang, 2016). The goal of our study is to begin to answer Cochrane's call using 94 characteristics from CRSP, Compustat and I/B/E/S; one-month ahead U.S. returns during 1980-2014; and empirical methods that avoid overweighting microcap stocks (Fama and French, 2008; Hou, Xue and Zhang, 2016) and that adjust for data snooping biases (Harvey, Liu and Zhu, 2016).

Our approach follows that of Fama and French (1992) and others in that we estimate Fama-MacBeth regressions. However, we fundamentally diverge from the anomalies literature where characteristics have almost always been evaluated singly or with very few controls by simultaneously including all 94 characteristics as explanatory variables, and by evaluating the stability of the return generating process over calendar time. Our method is feasible because the mean absolute correlation across characteristics is small (0.07), and because we retain all firm-month observations by setting missing characteristic values to the standardized mean of that month's non-missing values.

To establish a baseline against which to compare the results of our approach, we first estimate three sets of regressions over our full data window 1980-2014 as a whole: Regressions that contain each of the 94 characteristics as a single independent variable; regressions that are the characteristics versions of the prominent benchmark factor models of Carhart (1997), Fama and French (2015) and Hou, Xue and Zhang (2015); and regressions that add one and only one of the characteristics that are not in the benchmark models to the benchmark model specifications. We seek to avoid overweighting microcap stocks (Hou, Xue and Zhang, 2015) by estimating our regressions using market-value-weighted least squares (VWLS) on all stocks, and OLS on all-but-microcap stocks. Mindful of data snooping concerns, we define a characteristic as being statistically significant only when the absolute value of its Fama-MacBeth *t*-statistic is greater than or equal to 3.0 (Harvey, Liu and Zhu, 2016).

In our baseline regressions, we find that only 4 of the 94 characteristics we study are significant when the Fama-MacBeth regressions contain one and only one characteristic and the broad cross-section is measured using VWLS on all stocks, and that 17 characteristics are significant when OLS is applied to all-but-microcaps. Next, estimation of the characteristics versions of benchmark factor models reveals that two of the four characteristics in the Fama-French five-factor model, and two of the three characteristics in the Hou, Xue and Zhang *q*-factor model, are significant for both measures of the broad non-microcap cross-section of firms, while no characteristics are significant in the three-factor Carhart model. Then extending the benchmark models by adding additional characteristics to the benchmark models one at a time yields 15, 8 and 3 significant characteristics for the Carhart, five-factor and *q*-factor models using VWLS on all stocks, and 25, 8 and 3 significant characteristics using OLS on all-but-microcaps. We interpret these results as indicating that within the set of purposely low-dimension benchmark models, Hou, Xue and Zhang's *q*-theory model best captures the independent determinants of average returns in that it yields the fewest incrementally significant firm characteristics beyond those it itself dictates.

We next relax the approach of evaluating non-benchmark model firm characteristics one at a time by simultaneously including all 94 characteristics in the Fama-MacBeth regressions. We argue that this enables us to most powerfully identify both the independent determinants of returns and the characteristics that have insignificant partial correlations with returns. Using this method, we estimate that 8 characteristics are independent determinants in the non-microcap cross-section of stocks as measured by VWLS on all stocks, and that 12 characteristics are determinants using OLS on all-but-microcaps. We note that assessing whether 8-12 independent determinants is a large or a small number is unclear. On the one hand, 8-12 is materially larger than the dimensionality of the benchmark models. On the other hand, 8-12 is just 9%-13% of the 94 firm characteristics we study, meaning that 82-88 or 87%-91% of characteristics are statistically insignificant. We also note that the identities of the 8-12 independent determinants of returns identified by the simultaneous-inclusion method lie largely outside those of the Carhart, five-factor and *q*-factor benchmark models, with only three of the six benchmark model characteristics overlapping with the 8-12 characteristics we find to be the independent determinants of the cross-section of one-month ahead returns over the period 1980-2014.

Our last sets of results add entirely new color to the preceding high-level aggregate perspective by documenting that there are striking differences in the number and economic importance of the independent determinants of returns over calendar time. Specifically, we show that 2003 is a watershed year in that across all sizes of firms only half as many characteristics determine returns after 2003 as before 2003, and the characteristics-based predictability of returns drops suddenly and persistently in 2003, especially in the broad cross-section of non-microcap stocks. We find that just 1-2 of the 94 characteristics are reliably identified as independent determinants of returns after 2003 as compared to 11-16 characteristics before 2003. In term of economic magnitudes, the mean raw monthly hedge return from exploiting predictability in the set of 94 characteristics declines from 1.9% (*t*-statistic = 4.4) before 2003 to 0.5% (*t*-statistic = 1.1) after 2003 the VW all-stocks hedge portfolio (*t*-statistic on the difference in mean hedge returns of -1.4% = -2.3), and from 2.8% (t-statistic = 5.7) before 2003 to 0.1% (t-statistic = 0.2) after 2003 (t-statistic on the difference in mean hedge returns of -2.7% = -4.4) in the EW all-but-microcap stocks hedge portfolio. Similar results obtain after controlling for the factor returns called for in the Carhart, five-factor and q-factor benchmark factor models. Although we do not tightly identify the reason for the sudden drop in predictability, we note that a number of changes occurred in the information and trading environment during July 2002-June 2003, including the passing of the Sarbanes-Oxley Act, the accelerating of 10-Q and 10-K filing requirements by the SEC, and the introduction of autoquoting by the NYSE. While the temporal confluence of these changes makes it difficult to causally identify one or more of them with the shifts we observe in the monthly return generating process, we propose that the changes made it cheaper and technologically easier to rapidly implement quantitative long/short trading strategies. Thus, consistent with the costly-limits-to-arbitrage arguments of Shleifer and Vishny (1997), Lesmond, Schill and Zhou (2004), Chordia, Roll and Subrahmanyam (2008), Li and Zhang (2010) and Lam and Wei (2011), we conjecture that the 2002-2003 changes in the information and trading environment increased arbitrage activity, increased the efficiency of the stock market, and to the degree that the significant pre-2003 pricing of characteristics reflected high costly limits to arbitrage, decreased the influence of characteristics in determining average returns after 2003.

In its implications, our study adds a third reason to those of Harvey, Liu and Zhou (2016) and McLean and Pontiff (2016) for why the hundreds of stock return anomalies reported in prior studies warrant skepticism. Beyond data snooping and post-publication decay, we show that despite the average cross-correlation in characteristics being a low 0.07, since 2003 almost no characteristics-based anomalies have existed in the non-microcap cross-section of returns. We think this presents a challenge to future work in the anomalies literature. We also propose that the sensitivity of returns to the number and identity of characteristics that matter in explaining the cross-section pre- versus post-2003 means that future empirical models of average returns could benefit from weighting post-2003 data more strongly (or even exclusively) relative to pre-2003 data.

2. Extant Literature on Firm Characteristics and the Cross-Section of Stock Returns

Our study is related to three main areas of research. The first is work that models average returns as a function of firm characteristics or exposure to systematic factors. Papers in this area have concluded that factor models based on a small number of characteristics are largely able to explain the portfolio returns formed by individually ranking firms on a large number of characteristics (Hou, Xue and Zhang, 2015; Fama and French, 2015, 2016). For example, motivated by q-theory, Hou, Xue and

Zhang (2015) find that a factor model consisting of the excess market return, a small-minus-big size factor, a high-minus-low investment factor, and a high-minus-low return on equity factor performs similarly to a model featuring size, book-to-market, and 12-month momentum but also captures many patterns not explained by the three factors. Hou, Xue and Zhang therefore propose that their four-factor model is a powerful alternative to other factor models and that any new anomaly variable warrants being benchmarked against their *q*-factor model to determine if the anomaly truly provides any incremental information. In a related approach, Fama and French (2015, 2016) develop a five-factor model that augments the three-factor model of Fama and French (1993) by adding profitability and investment factors (Li, Livdan and Zhang, 2009; Novy-Marx, 2013). Taking a different approach entirely, Light, Maslov and Rytchkov (2016) treat expected returns as latent variables and develop a procedure that distills 13 factors based on specific characteristics into two new factors, one of which they argue summarizes the information from all anomalies.

A second area of research that our work connects to examines the predictability of returns. Prior studies find that return predictability is strongest among stocks with the highest levels of arbitrage frictions and has declined over time as arbitrage frictions have declined and arbitrage activity has risen. Lesmond, Schill and Zhou (2004), Hou and Moskowitz (2005), Chordia, Roll and Subrahmanyam (2008), Li and Zhang (2010) and Lam and Wei (2011) all report that firm characteristics predict returns primarily among stocks with high trading costs or arbitrage frictions. Consistent with this view, Schwert (2003), Green, Hand and Soliman (2011), Hendershott, Jones and Menkveld (2011), Chordia, Subrahmanyam and Tong (2014) and McLean and Pontiff (2016) find that returns to various characteristic-based anomalies decline in response to greater arbitrage activity or as anomalies are made public. Most recently, Novy-Marx and Velikov (2016) observe that while returns to low turnover strategies are robust to adjustments for trading costs, many higher turnover strategies are not.

The third area our research speaks to is studies that have sought to measure the dimensionality of returns, primarily using firm characteristics, either indirectly by cataloging the characteristics that have been found to be significant using no- or low-dimensional control methods, or directly by placing medium-sized sets of characteristics into multidimensional models. Illustrating the catalog approach, Subrahmanyam (2010) identifies 50 significant characteristics; Green, Hand and Zhang (2013) list 330 characteristics in the anomalies literature; Harvey, Liu and Zhu (2016) itemize 315 such characteristics and/or factors; and Hou, Xu and Zhang (2016) further expand the set of anomaly-based firm characteristics to 430+. Illustrating instead the multidimensional perspective, Jacobs and Levy (1988) analyzed 25 characteristics and found that 10 were significant, and work by Haugen and Baker (1996) reported that 11 of the 40 interrelated characteristics they study were significant.[1] From sets chosen based on published research, Fama and French (2008) and Lewellen (2015) found that 7 out of 7, and 10 out of 15 characteristics, respectively, were significant.[2]

Notwithstanding prior research in the areas described, the challenge issued by Cochrane (2011) remains: only a fraction of the 430+ characteristics in the anomalies literature have been studied in a way that powerfully identifies which firm characteristics provide *independent* information about average returns, and which characteristics are redundant because they are incrementally insignificant. Our paper responds to Cochrane's challenge by simultaneously evaluating a much larger set of characteristics than prior work, and in that larger set estimating not just the number, identity and economic significance of the independent determinants, but newly highlighting the degree to which results obtained over the full data period 1980-2014 vary over calendar time and by firm size.

3. Dataset Construction and Correlations among Firm Characteristics

3.1 Dataset aligned in calendar time

Since the chief goal of our paper is to empirically identify the independent determinants of average returns by regressing one-month-ahead returns on a large number of characteristics all at the same time, we face design decisions as to which and how many characteristics to include; how to combine characteristics across firms, time periods and databases; and how to address missing data. To maximize the ability of others to replicate and/or expand our work, we seek to transparently detail the choices we make in selecting, aligning and coding up firm characteristics. In doing so, we recognize that some choices we make distance us from the exact research designs, characteristics definitions and sample periods used in the papers in which the firm characteristics were originally identified.

We initially selected 102 of the 330 characteristics listed in Green, Hand and Zhang (2013), requiring that each characteristic be calculable entirely from CRSP, Compustat and/or I/B/E/S data.[3] Our data covers the 35-year period January 1980–December 2014. We begin in 1980 because most characteristics only become robustly available in that year. The 102 characteristics we select are listed in Table 1. Details of each characteristic, including a description of how it is calculated and the

[1] Many of the 40 characteristics used by Haugen and Baker (1996) are highly correlated variants of a few constructs, with the likely result that the analysis in Haugen and Baker is based on fewer than 40 independent characteristics.

[2] Fama and French (2008) orient their analysis around whether the significance of characteristics is robust across firm size. Lewellen (2015) focuses his work on the cross-sectional dispersion and out-of-sample predictive ability of the stock return forecasts that he extracts from the 15 characteristics he studies.

[3] We also restricted the firm characteristics to main-effect signals. We do not include characteristics that are interactions between other characteristics.

author(s), journal, and year of publication or working paper of the underlying academic study, are shown in Appendix 1. The characteristics span both highly and sparsely cited papers; published and working papers; and publication dates between 1977 and 2016. On occasion, more than one characteristic comes from a given paper.

We begin our data creation with all firms with common stock on the NYSE, AMEX or NASDAQ that have a month-end market value on CRSP and a non-missing value for common equity in their annual financial statements. We then integrate data across Compustat, I/B/E/S and CRSP, and compute and align characteristics in calendar time. Since Green, Hand, and Zhang (2013) report that 57% of the 330 characteristics they list are evaluated by the original authors through the lens of monthly returns, we re-measure and re-align characteristics every month. For each month t's return we calculate characteristics as they were at the end of month t-1, assuming that annual accounting data are available at the end of month t-1 if the firm's fiscal year ended at least six months before the end of month t-1, and that quarterly accounting data are available at the end of month t-1 if the fiscal quarter ended at least four months before the end of month t-1. I/B/E/S and CRSP data are aligned in calendar time using the I/B/E/S statistical period date and the CRSP monthly or daily end date.

While monthly updating is consistent with the portfolio rebalancing approach used by many quantitative institutional investors, we recognize that some practitioners update their data as often as every minute, or as infrequently as every 12 months. We choose monthly updating because we view it as a reasonable tradeoff between the lower transactions and trading costs of longer frequencies, and the benefit of greater timeliness (Novy-Marx and Velikov, 2016). Our choice means that those characteristics in our dataset that come from studies with a shorter-than-monthly frequency will be less timely than in the original studies, while those that come from studies using longer frequencies will be more timely. Such slippage may lower our ability to detect the incremental significance of individual characteristics but it also reduces the chances that we will identify return predictability that does not survive the trading cost effects of high turnover strategies (Novy-Marx and Velikov, 2016).

We take monthly stock returns from CRSP and include delisting returns per Shumway and Warther (1999). We delete 20 observations that have a monthly return less than -100%, and set blank values of analyst following *nanalyst* to zero. I/B/E/S is the most restrictive of our databases in its coverage of firms and availability over time, so we only use I/B/E/S-based characteristics starting in January 1989 because that is when I/B/E/S' more expansive coverage begins.[4] Following prior work such as Hou, Xue and Zhang (2015) and Fama and French (2015), we delineate firm size groupings

[4] The firm characteristics that employ I/B/E/S data are *sue*, *chfeps*, *fgr5yr*, *sfe*, *nanalyst*, *disp* and *chnanalyst*.

based on their monthly NYSE-based percentiles. We label stocks with a market cap greater than the median NYSE stock at the end of month t-1 as big, stocks below the median and above the 20th percentile as small, stocks with values less than or equal to the 20th percentile as microcap, and stocks excluding microcaps as all-but-microcap.

Since in our key analyses we identify the independent determinants of average returns by regressing one-month-ahead returns on all characteristics simultaneously, in such regressions we avoid discarding the characteristic simply because its value is missing in one or more firm-months. Just 4% of characteristics have full data with no missing observations over Jan. 1980–Dec. 2014. The approach we take to retaining as much characteristic information as possible is to first winsorize all characteristics at the 1st and 99th percentiles of their monthly distributions and standardize each to have a zero mean and unit standard deviation. We then set missing characteristic values to the characteristic's post-standardized monthly mean of zero.[5] In Table 2 for each firm characteristic we report the number of our dataset of 1,933,898 firm-month observations over the period Jan. 1980–Dec. 2014 with non-missing data, and the percentage that are missing before being reset to zero. We note that the characteristics with the largest fraction of missing data tend to be those that use I/B/E/S analyst information (*chfeps, chnanalyst, disp, fgr5yr, nanalyst, sfe*) or that use sparsely populated Compustat data (*rd_mve, rd_sale, realestate*).

3.2 Correlations among firm characteristics

We gauge the potential for multicollinearity concerns in our Fama-MacBeth regressions by measuring the cross-correlations among our initial set of 102 firm characteristics. While multicollinearity does not lead to bias in estimated slope coefficients, it does increase their standard errors. Thus, to the extent we are able to exclude characteristics with very large cross-correlations with other characteristics because they are mechanically or economically related—for example, beta and beta squared—we expect to be able to more powerfully identify the independent determinants of average returns when we estimate regressions that simultaneously contain very large numbers of characteristics, especially if the number of highly collinear characteristics is found to be small.

We therefore calculate the variance inflation factors (VIFs) of each characteristic since VIFs summarize the extent to which a given characteristic is explained by a linear combination of all other characteristics (Greene, 2011). Panel A of Table 3 describes the distribution of VIFs. While the

[5] The approach of replacing missing independent variables with their sample means is known as the zero-order regression method (Wilks, 1933). Under multivariate normality of the dependent and independent variables, the zero-order method is generally expected to lead to unbiased slope coefficient estimates (Afifi and Elashoff, 1966).

median VIF of 1.8 is not large, VIFs are right-skewed in that 10% of characteristics have a VIF ≥ 9.8. We therefore seek to mitigate the effects of multicollinearity in our key regressions that simultaneously include all characteristics by removing the eight characteristics that are most strongly related to other characteristics (*betasq, dolvol, maxret, mom6m, pchquick, quick, stdacc* and *lgr*), each of which has a VIF > 7. We then use the remaining 94 characteristics throughout our analyses.[6]

In panel B of Table 3 we report the key percentiles of the absolute cross-correlations among characteristics before and after removing the eight characteristics with VIFs greater than 7. In both cases, the mean and median absolute cross-correlations are quite low at 0.07 and 0.03, respectively.[7] Not surprisingly, after removing characteristics with VIFs > 7, the largest cross-correlations also decline. Panel C shows the distribution of the absolute cross-correlations among the 94 non-highly-cross-correlated characteristics, making clear that 90% of absolute cross-correlations are below 0.2.

4. Results

We estimate standard Fama and MacBeth (1973) regressions over the period 1980–2014 to determine how many and which firm characteristics are significant when they are included as determinants of one-month-ahead returns. We observe the mean estimated coefficients on included characteristics, and calculate their *t*-statistics from the time-series of mean monthly coefficient estimates, given Newey-West adjustments over 12-monthly lags.

To establish a baseline against which to compare these results, we begin by estimating three restricted sets of regressions over our data window 1980-2014. First, we estimate the characteristics-based versions of the Carhart, five-factor and *q*-factor factor models. Second, we expand the number of characteristics that are analyzed beyond the 3-4 in each of the benchmark models by adding one and only one characteristic to those dictated by the benchmark models. Third, we simultaneously include all 94 characteristics into one set of Fama-MacBeth regressions. We argue that the third approach is the one that enables us to most powerfully identify the independent determinants of average monthly

[6] In untabulated analyses, we vary the VIF cutoff at which we exclude a characteristic from 5 to 10, and find very similar results to those obtained using our default VIF cutoff of 7. Our results are also similar if we do not exclude any characteristics based on VIF cutoffs at all.

[7] The mean absolute cross-correlation among characteristics is similarly small if cross-correlations are calculated after missing characteristic values are reset to each characteristic's monthly mean. (Panels B and C use characteristics that may have missing values, while the pooled regression to calculate VIFs uses characteristics that have had missing values set to their monthly mean value.)

returns because it avoids creating omitted correlated variable bias in characteristic coefficient estimates by virtue of not omitting any characteristics.[8]

In assessing whether a characteristic is reliably related to average returns, we are mindful of recent criticisms that have been made about the inferential biases that can arise in tests of asset pricing models stemming from data snooping (Harvey, Liu and Zhu, 2016) and the overweighting of microcap stocks that make up on average only about 3% of the market cap of the NYSE-Amex-NASDAQ universe (Fama and French, 2008; Hou, Xue and Zhang, 2016). We seek to avoid the former bias by following the recommendation of Harvey, Liu and Zhu (2016) to only infer that a mean monthly estimated coefficient is statistically significant when the absolute value of its Fama-MacBeth *t*-statistic is greater than 3.0.[9] We seek to avoid the latter bias by focusing the majority of our analyses on the non-microcap cross-section of firms, implemented in two ways: by applying value-weighted least squares to all stocks, and by using OLS on all-but-microcap stocks.

4.1 Estimating the benchmark models of returns

The characteristics we use in the characteristics-based benchmark models are size *mve*, book-to-market *bm* and 12-month momentum *mom12m* for the Carhart model; size *mve,* book-to-market *bm*, investment *agr* and operating profitability *operprof* for the 5-factor model; and size *mve,* investment *agr* and quarterly return-on-equity *roeq* for the *q*-factor model. Table 4 reports the results of estimating the benchmark models over the full period 1980-2014. Using the Harvey, Liu and Zhu (2016) data snooping adjusted *t*-statistic cutoff of 3.0 or more, for the Carhart model in panel A we find that only *bm* is significant and only when OLS is applied to all stocks (which overweights microcaps). In the five-factor model in panel B, *mve* and *bm* are never significant but *agr* and *operprof* are always significant. In the *q*-factor model shown in panel C, *agr* and *roeq* are always significant except when microcaps are excluded. We interpret these baseline results as indicating that within the set of purposefully low-dimensioned characteristics-based versions of prominent benchmark factor models, the five-factor and *q*-factor models outperform the Carhart model in identifying significant individual determinants of average returns, especially when microcap stocks are excluded.

[8] This assumes that all the independent determinants of average returns are in the set of 94 characteristics we use.

[9] We note that an additional advantage to our using an absolute *t*-statistic cutoff of 3.0 finesses the need to explicitly adjust for the number of *t*-statistics expected purely by chance because the number of *t*-statistics expected to be significant using a two-tailed *t*-statistic for 94 independent variables is just 0.33. Other approaches taking this issue into account, such as Bonferroni (1935) adjustments to p-values would yield a statistical cutoff similar to the absolute *t*-statistic cutoff of 3.0 proposed by Harvey, Liu, and Zhu (2016).

4.2 Estimating the effects of single characteristics

In Table 5 column A we detail the results of placing each characteristic individually into its own Fama-Macbeth regression over the full period 1980-2014, followed in columns B-D by the results of adding each characteristic one at a time to those specified by each of the three benchmark models. In each column we report results for all stocks using WLS, all-but-microcap stocks using OLS, and for purposes of comparison to much of the anomalies literature, all stocks using OLS. For visual emphasis, *t*-statistics with an absolute *t*-statistic ≥ 3.0 are shown bolded and boxed, while *t*-statistics ≥ 1.96 in absolute value are bolded but not boxed. The number of absolute *t*-statistics ≥ 3.0 and ≥ 1.96 are shown in the first and second lines of Table 5. To recall, we only infer that a characteristic's *t*-statistic is significant when its absolute value ≥ 3.0; *t*-statistics ≥ 1.96 are provided for descriptive purposes only.

As judged by *t*-statistics, in column A we find that 4 of 94 characteristics are significant in univariate regressions for the cross-section of firms as measured by VWLS on all stocks, while 17 characteristics are significant using OLS on all-but-microcaps. Attesting to the disproportionate number of independent determinants in microcap stocks, there are 35 significant *t*-statistics when microcaps are given the same regression weighting as larger stocks (all stocks, OLS). Comparing the number of *t*-statistics with absolute values ≥ 3.0 versus ≥ 1.96 affirms the conclusions of Harvey, Liu and Zhang (2016), but also highlights a new finding, namely that the effects of data snooping are disproportionately felt in large cap stocks, since the difference between lines 1 and 2 of Table 5 is largest when regressions are estimated using VWLS on all stocks (4 *t*-statistics with absolute values ≥ 3.0 versus 26 *t*-statistics with absolute values ≥ 1.96).

Next, columns B-D show that when added one at a time to the Carhart, five-factor and *q*-factor models, 15, 8 and 3 characteristics are incrementally significant using VWLS on all stocks, and 25, 8 and 5 characteristics are incrementally significant using OLS on all-but-microcaps.[10] Since columns B-D also show that the *q*-factor model leads to the fewest number of significant characteristics outside of those in the benchmark model itself, we conclude that of the three purposefully low-dimensioned benchmark models, the *q*-factor model best captures the cross-sectional variation in average returns

[10] In Column A, the number of absolute *t*-statistics ≥ 3.0 is 4 for All stocks, VWLS. This number appears surprisingly low in part because 7 characteristics have |t-statistics| very close to but just below 3.0 (viz., *t*-statistics = 2.9 or 2.8). Comparing the numbers of absolute *t*-statistics ≥ 3.0 or ≥ 1.96 reported in Column A versus Columns B-D, we note the counterintuitive finding that Column B tends to have more significant *t*-statistics Column A. One reason for this could be that if characteristics are measured with error, some characteristics that were insignificant when estimated in a univariate manner become significant because the Carhart (Column B) and Fama-French characteristics control for the noise (Jacobs and Levy, 1988).

due to the 94 characteristics we study.[11] Our conclusion echoes that of Hou, Xue and Zhang (2015, 2016) who conduct similar tests but using the factor version of the *q*-factor model.

4.3 Identifying the independent determinants of the cross-section of average U.S. monthly returns by simultaneously including all 94 characteristics in Fama-MacBeth regressions

Table 6 presents the results of relaxing the approach in Table 5 of evaluating non-benchmark model characteristics one at a time by instead simultaneously including all 94 characteristics in Fama-MacBeth regressions over the full period 1980-2014. We argue that this approach enables us to most powerfully identify the independent determinants of returns (and the characteristics that have insignificant partial correlations with returns) because it makes every characteristic to compete against every other characteristic. The expected result is that only those characteristics that are truly independent determinants of returns will have significant estimated coefficients when all other characteristics are controlled for. As in Table 5, the number of absolute t-statistics ≥ 3.0 and for descriptive purposes ≥ 1.96 are shown in the first and second lines of the table, respectively. Per the reasoning and implementation described in the last paragraph of section 3.1, in Table 6 missing characteristic values have been replaced by zeros.

Table 6 shows that after controlling for data snooping biases per Harvey, Liu and Zhu (2016), 8 characteristics are found in Column A to be independent determinants when the cross-section of stocks is measured using VWLS applied to all stocks, rising to 12 characteristics in Column B using OLS on all-but-microcaps. As in Tables 4 and 5, the disproportionate influence of microcap stocks can be seen in Table 6 by noting that applying OLS to all stocks yields a total of 27 independent determinants in Column C, more than double the 12 in Column B seen when microcaps are excluded.

In interpreting these results, we note that it is unclear whether 8-12 independent determinants is a large or small number. On the one hand, 8-12 is markedly larger than the number of significant characteristics found for the best performing *q*-factor benchmark model in Table 5. On the other hand, 8-12 independent determinants represents just 9%-13% of the 94 firm characteristics, meaning that 82-88 or 87%-91% of characteristics are insignificant and thus redundant. In this sense our results add further skepticism about the validity of the vast anomalies literature to that raised by Harvey, Liu and

[11] In Table IA-2 of our Internet Appendix, we report the results of repeating the analysis in Table 5 using risk-adjusted returns obtained using the approach in Brennan, Chordia and Subrahmanyam (1998) for the three benchmark factor models, and we find similar results in that the *q*-factor model yield the fewest overall significant characteristics. In Table IA-3 we also show that we find very similar results if we estimate the regressions in Table 5 after replacing missing characteristic values with zeros, as we do in Table 6.

Zhou's (2016) data snooping critique and the post-publication decay concerns raised McLean and Pontiff (2016).

We highlight two other findings in Table 6. First, some characteristics that have received little focus in the anomalies literature, such as *ear* and *nincr*, perform as well as or better than the characteristics in the benchmark models. Out of the total of six benchmark model characteristics, only *agr*, *bm* and *mve* are significant in the non-microcap cross-section of stocks when all 94 characteristics are made to compete against each other, and never across all measures of stock market breadth. In contrast, *cash*, *ear*, *mom1m*, *nincr*, and *retvol* have significant estimated coefficients across all three measures of stock market breadth. Most significant coefficients are also fairly stable across different samples and approaches, with the characteristics that are significant for all stocks using WLS also tending to be significant for all-but-micro stocks OLS and for all stocks OLS.

Second, inspection of the significance of individual coefficients lends weight to an additional view for why simultaneously including all 94 characteristics is a powerful way to identify independent determinants of returns. This is the proposition that including more and more characteristics may better control for the error that exists in the measurement of characteristics, with the result that some characteristics that were insignificant when estimated in a univariate or low-dimensioned manner because they were measured with a great deal of noise become significant when estimated in a high-dimensioned manner that helps controls for the noise (Jacobs and Levy, 1988). For example, in Table 5 *bm* is insignificant estimated in a univariate manner (column A) and when competing against the *q*-factor benchmark model characteristics (column D), whereas in Table 6 *bm* is significant when all 93 other characteristics are included in its regression. In contrast, characteristics such as *ill* or *invest* that are significant in Table 5 are no longer significant in Table 6.

To address the concern that the results in Table 6 are due to simultaneously including the very large number of 94 characteristics that we do, in Table 7 we report the results of reducing the number of characteristics that are simultaneously included to the 28 that have am absolute *t*-statistic >= 3.0 in at least one of Columns A, B and C of Table 6. Using this subset of 28 characteristics, we then re-estimate the regressions of Table 6. Table 7 shows that in terms of the number of significant *t*-statistics, this method yields similar results to those in Table 6, in that 7 and 9 of the 28 characteristics are simultaneously significant for VWLS applied to all stocks and OLS applied to all-but-microcap stocks, respectively, and 24 characteristics are significant when OLS is applied to all stocks.

Overall, we conclude from Tables 5 - 7 that while benchmark model characteristics *agr*, *bm* and *mve* capture some of the predictability in one-month ahead returns over the full period 1980-2014 as a whole, a larger total of 8-12 of the 94 characteristics we study reliably provide independent information about average monthly U.S. stock returns, using methods that seek to avoid overweighting microcaps and that adjust for data snooping.

4.4 Hedge portfolio returns to predicting the cross-section of returns using all 94 characteristics

Since statistical significance does not necessarily translate into economic importance, in this section we report the results of hedge portfolio tests aimed at measuring the magnitude of the economic benefits to exploiting the full set of characteristics when predicting the cross-section of one-month ahead returns. Specifically, following the method of Lewellen (2015), in panel A of Table 8 we report the magnitude and significance of three mean one-month holding period out-of-sample hedge portfolio raw returns that are calculated as follows. For every month t-1 starting in Jan. 1990 we use data from month t-120 through t-1 to estimate the same three sets of regressions as those reported in columns A, B and C of Table 6. As in Tables 4-7, we assume that annual accounting data are available at the end of month t-1 if the firm's fiscal year ended at least six months before the end of month t-1. Separately for the set of stocks defined in each column, on a firm-by-firm basis we then apply the resulting mean coefficient estimates to the values of the corresponding 94 characteristics as of the end of month t-1. This yields three predicted returns for month t for each firm, one per each of columns A, B and C. Then we calculate the realized return to each of three hedge portfolios for month t using two types of breakpoints for identifying firms in the top and bottom deciles of predicted returns, and two methods of weighting the individual realized returns within each decile. For the column A portfolio in panel A of Table 8, denoted portfolio A, decile breakpoints are based on only NYSE firms (so there are an equal number of NYSE stocks in each decile, but not necessarily an equal number of stocks across the NYSE, AMEX and NASDAQ combined) and the realized returns in the top/long and bottom/short deciles are weighted by firms' market caps at the end of month t-1. For the column B portfolio, referred to as portfolio B, the decile breakpoints are based on all-but-microcap stocks and the realized returns in the top/long and bottom/short deciles are equally-weighted. Lastly, for the column C portfolio, denoted portfolio C, the decile breakpoints are based on NYSE stocks and the realized returns in the top/long and bottom/short deciles are equally-weighted. Since predicted returns are available for each firm at the end of each month, our approach is in theory implementable in real time using only historically available data.[12] In total, applying this method yields a time series of 274 realized raw monthly hedge returns over the period Jan. 1990-Dec 2014 for each of the three hedge portfolios.

[12] We confirm that our approach is only quasi-out-of-sample, since we use characteristics that were not first reported in the academic literature until after month t-1. However, potentially counterbalancing some the upward bias in implementable hedge returns that such data snooping creates, we never discard a characteristic, even when an

Panel A of Table 8 reports descriptive statistics for the realized raw monthly hedge portfolio returns. Inspection shows that the mean raw returns for all three types of hedge portfolios are always statistically and economically large. For the cross-section of stocks measured by portfolio A's VW all stocks long top / short bottom decile hedge portfolio with NYSE decile breakpoints, the mean raw monthly return over 1990-2015 is 1.2% (*t*-statistic = 3.8), while for the cross-section of stocks measured by portfolio B's EW all-but-microcaps hedge portfolio using all-but-microcaps decile breakpoints the mean monthly raw return is 1.4% (*t*-statistic = 4.5). Once more highlighting the disproportionate influence that microcaps can exert, the mean monthly raw return for portfolio C's EW all stocks hedge portfolio with NYSE decile breakpoints is 3.1% (*t*-statistic = 11.3).

Since raw hedge portfolio returns in the anomalies literature are often orthogonalized against key factor returns, in panel B we report the estimated alpha intercepts and associated *t*-statistics from regressing the raw hedge portfolio returns described in panel A on the factor returns relevant to each of the Carhart, five-factor and *q*-factor models. The estimated alphas in panel B are similar in magnitude and significance to the mean raw hedge returns found in panel A. Moreover, the *q*-factor model always has the smallest alpha (eliminating more of the mean raw hedge return) than either the Carhart or five-factor models, supporting the inference we made from Table 5 that of the benchmark models, Hou, Xue and Zhang's *q*-factor model best captures the cross-sectional variation in returns due to the truly independent determinants of average returns.

In sum, the mean hedge returns detailed in Table 8 show that even for non-micro-cap stocks, the economic importance of the predictability in one-month-ahead U.S. returns arising from the 8-12 independent determinants averaged over the full period 1980-2014 has been substantial.

4.5 The 2003 change in predictability and the pre- versus post-2003 differences in the number and economic importance of the independent determinants of average monthly U.S. stock returns

Consistent with almost all research in the anomaly and asset pricing literatures, the results described in Tables 4-7 treat the years 1980-2014 as a uniform block of calendar time during which the return generating process is presumed to remain constant in calendar time. We now relax this assumption in light of the substantial changes in the volume, nature and costs of trading in stocks that occurred during 1980-2014, including Reg. FD, the decimalization of trading quotes, Sarbanes-Oxley, accelerated SEC filing requirements, autoquoting, and computerized long/short quantitative

estimated coefficient would indicate that the characteristic is either no longer incrementally significant or is significant but with a sign opposite to that expected based on the anomalies literature.

investment (Chordia, Roll and Subrahmanyam, 2001; Jones, 2002; Schwert, 2003; French, 2008; Green, Hand and Soliman, 2011; Hendershott, Jones and Menkveld, 2011).

The first approach we take to assessing the constancy of the return generating process in calendar time is shown in Figure 1 where we plot the natural log of 1 plus the cumulative mean raw hedge portfolio returns calculated in a manner equivalent to those in panel A of Table 8, but where the seven characteristics that require I/B/E/S data have been excluded because I/B/E/S data is only robustly available starting in 1990. Visual inspection of Figure 1 strongly suggests that the mean hedge return for each of the three portfolios displayed fell sharply and persistently in late 2002 / early 2003. Indeed, the declines are so marked for the non-microcap cross-section of stocks that the characteristics-based predictability of one-month ahead U.S. returns has been on average zero since early 2003, leaving economically meaningful predictability only in microcaps, and there to a much reduced degree.

We provide statistical evidence consistent with these visual assessments in Table 9, where in panels A and B we report the mean raw hedge returns and the alphas from factor-orthogonalized returns, together with their associated *t*-statistics, for each of the three hedge portfolios pre-2003, post-2003, and post- versus pre-2003. We define pre-2003 as the period ending Dec. 31, 2002 and the post-2003 period as starting Jan. 1, 2003. Panel A shows that the mean raw monthly hedge return in the VW all stocks hedge portfolio with NYSE decile breakpoints declines from 1.9% before 2003 (*t*-statistic = 4.4) to 0.5% after 2003 (*t*-statistic = 1.1), with the fall of -1.4% per month being reliably negative (*t*-statistic = -2.3). Similarly the mean raw monthly hedge return for the EW all-but-micro hedge portfolio with all-but-micro decile breakpoints drops from 2.8% before 2003 (*t*-statistic = 5.7) to 0.1% after 2003 (*t*-statistic = 0.2), with the post- versus pre-2003 decline of -2.7% being reliably negative (*t*-statistic = -4.4). In contrast, while the mean raw monthly return for the EW all stocks hedge portfolio with NYSE decile breakpoints also declines by a significant -2.8% post- versus pre-2003 (*t*-statistic = -5.2), it remains reliably positive in the post-2003 period with a mean of 1.7% per month (*t*-statistic = 4.4). Panel B shows that with the exception of Portfolio A of the Carhart factor model, similar results obtain after controlling for the factor returns specified in the Carhart, five-factor and *q*-factor models.

Table 10 presents the second method we use to assess the inter-temporal constancy of the return generating process. Specifically, Table 10 reports the results of estimating the same Fama-MacBeth regressions as in Table 6, but separately for the approximately equal subperiods 1980-2002 and 2003-2014. Consistent with the marked declines visible in the raw and factor-orthogonalized hedge returns seen in Figure 1 and Table 9, Table 10 shows that the number of independent characteristics-based determinants of average returns drops from 11 to 2 for all stocks using VWLS, from 16 to 1 for all-but-microcaps using OLS, and from 25 to 13 for all stocks using OLS.[13] While there remains predictability in microcap stocks after 2003, outside of such microcaps that make up only 3% of the total value of the U.S. stock market, virtually all of the 94 characteristics we study have been statistically and economically irrelevant in predicting one-month ahead U.S. returns since 2003.

We interpret the sharp shift in late 2002 / early 2003 in the number and economic importance of the independent determinants of the monthly return generating process, especially across firm size, as being consistent with the costly-limits-to-arbitrage arguments of Shleifer and Vishny (1997), Lesmond, Schill and Zhou (2004), Chordia, Roll and Subrahmanyam (2008), Li and Zhang (2010) and Lam and Wei (2011). We note that during the period July 2012 – June 2013, a number of changes occurred in the information and trading environment that made it cheaper and technologically more feasible to rapidly implement quantitative long/short trading strategies. Following the adoption of Reg. FD in Oct. 2000 and the decimalization of stock price quotes in Jan. 2001, both of which reduced effective spreads, price impact and trading costs (Bessembinder, 2003; Eleswarapu, Thompson and Venkataraman, 2004), the information environment changed in two ways. July 2002 saw the passing of the Sarbanes-Oxley Act that increased auditing quality requirements and imposed managerial responsibility on the quality of firms' internal controls for financial statements, beginning with those for fiscal 2002 that started to be reported in early 2003. Then the deadlines for when annual and quarterly reports had to be filed with the SEC following a fiscal year-end or quarter-end were accelerated starting in Nov. 2002 to make 10-Q and 10-K filings more timely. Importantly from a technological perspective, between Jan.-May 2003 the NYSE introduced its autoquoting software, a change that Hendershott, Jones and Menkveld (2011) argue led to dramatic reductions in the trading frictions and costs and an equally dramatic increase in the algorithmic trading that long/short equity hedge funds use to implement long/short quantitative trading strategies. While the temporal confluence of these changes makes it difficult to causally identify one or more of them as explaining the shifts

[13] In Tables IA-1, IA-4a and IA-4b of our Internet Appendix, we show that there is a similar drop in the number of significant characteristics when the analyses reported in Tables 4 and Table 5 are repeated pre- versus post-2003. Table IA-1 indicates that no benchmark model characteristics are significant in the non-microcap cross-section of stocks post-2003, while Tables IA-4a and IA-4b show that there is a similar drop in the number of significant characteristics when the analysis reported in Table 5 is repeated pre- versus post-2003. Thus when benchmark model characteristics are not controlled for and only one characteristic is incorporated into the Fama-MacBeth regressions, Tables IA-4a and IA-4b indicate that 10, 18 and 34 characteristics are significant pre-2003 for VWLS on all stocks, OLS on all-but-microcaps, and OLS on all stocks, respectively, but just 0, 1 and 10 characteristics are significant post-2003. When benchmark model characteristics are controlled for, we find that while pre-2003 the *q*-factor model yields just half the number of significant non-benchmark model characteristics as the next-best Fama-French five-factor model for regressions that avoid overweighting microcaps, after 2003 the number of significant non-benchmark model characteristics range between 0-2 for all three of the Carhart, Fama-French, and *q*-factor models.

seen in the monthly return generating process, we propose that in total the changes made it much cheaper and technologically easier to rapidly implement high volume quantitative long/short trading strategies, thereby increasing arbitrage activity, increasing the efficiency of the stock market, and to the degree that the statistically and economically significant pre-2003 pricing of characteristics reflected high costly limits to arbitrage, decreasing the number and influence of characteristics in determining average returns after 2003.[14]

4.6 Robustness tests

In this section, we summarize the results of additional analyses that are detailed in the Internet Appendix and that seek to assess the robustness of the results presented thus far. We undertake these additional analyses in part to address the concern that the results we report merely reflect the spurious fitting of noise, rather than documenting the presence of robust statistical and economic phenomena.

First, we re-estimate many of our regressions separately for big, small, and microcap stocks. The findings and inferences from these mutually exclusive size-based analyses are similar to those we present in the main results of the paper. For example, when we re-estimate Table 6 by applying VWLS to big, small and microcap stocks, we estimate that 4, 11 and 23 characteristics are independent determinants over the full period 1980-2014, as compared to 8, 12 and 27 in Table 6 for all stocks using VWLS, all-but-microcaps using OLS, and all stocks using OLS.[15] Also, when we re-estimate Table 10 by applying VWLS to big, small and microcaps separately, we find similar results to those in Table 10, namely that pre-2003 there were 4, 13 and 21 significant characteristics, respectively, whereas post-2003 there were 2, 4 and 11. Such results echo those of Table 6 in that they find [1] that there are half as many independent determinants post-2003 as compared to pre-2003; [2] just two independent determinants for large cap stocks post-2003 (out of the 94 total characteristics included in the Fama-MacBeth regressions); [3] post-2003 there remain 11 independent determinants in microcaps; and [4] both pre- and post-2003 it is the case that five times as many characteristics are significant in microcap stocks as in large cap stocks. Also, plots of the cumulative hedge returns

[14] We do not ascribe the shift in late 2002 / early 2003 to the post-publication reduction in the univariate mean hedge return documented by MacLean and Pontiff (2015). This is because we do not observe a spike in the number of anomalies either discovered or published in late 2002 / early 2003 (see Green, Hand and Zhang, 2013, Figure 1) and Harvey, Liu and Zhang (2016, Figure 1). We also differentiate our study from that of Chordia, Subrahmanyam and Tong (2014, CST) because while CST document an attenuation over calendar time in the returns to anomalies, they analyze only six anomalies, and test only for a linear or exponential decay in anomaly hedge returns.

[15] The results of these regressions are reported in Tables IA-5 and IA-6 of the Internet Appendix. We define stocks with a market cap greater than the median NYSE stock at the end of month t-1 as big, stocks below the median and above the 20th percentile as small, and stocks with values less than or equal to the 20th percentile as microcap.

analogous to those shown in Figure 1 but for big, small and microcap firms separately display similarly sharp changes in late 2002 / early 2003.[16]

Second, we conduct principal component analyses of the full set of 102 characteristics, and of the raw long/short hedge portfolio returns created for each firm characteristic. Consistent with the low 0.07 average absolute cross-correlation among characteristics, the number of principal components with eigenvalues greater than one is similar in magnitude to the number of characteristics we find to be significant in the Table 6 regressions. In Table IA-9 of our Internet Appendix we show the loadings of each characteristic and each hedge portfolio return on the first five principal components. Several of the most significant characteristics, for example *agr*, have strong loadings on the first few components. These supplementary findings support the conclusion that the 94 characteristics we study cannot be linearly collapsed down to a small number of latent factors, contrasting with other research that has argued that there to be only a small number of statistical factors in realized returns (Brown, 1989; Connor and Korajczyk, 1993).

4.7 Limitations

We recognize several caveats to and limitations of our research. While ours is the first to assess the simultaneous predictive power of a very large number of individual firm characteristics, we study only one quarter of the 430+ characteristics reported in the anomalies literature to date. As such, we likely do not identify all the truly independent determinants of average monthly returns. It may also not be appropriate to extrapolate our findings to the full population of 430+ characteristics because our approach has been to focus on those that can be calculated from CRSP, Compustat or I/B/E/S data, meaning that we have not sampled firm characteristics randomly from the population of characteristics. We may also have introduced measurement error through our approach to treating missing data and by aligning characteristics in calendar month time rather than in the daily or weekly time used in the original research. We also note that while in our quasi-out-of-sample tests we have sought to avoid using data that was unavailable in real time, implementing the positions dictated by our hedge portfolios would expose investors to potentially trading costs, especially in microcap stocks, such that the resulting net-of-trading-costs hedge returns might not be positive (Novy-Marx and Velikov, 2016).

[16] The plots are presented in Figure IA-1 and IA-2 of our Internet Appendix. Tables IA-7 and IA-8 conduct formal statistical tests of the mean raw and factor-orthogonalized hedge returns to big, small and microcap stocks pre- versus post-2003 in a manner analogous to Tables 8 and 9, respectively. The results in Tables IA-7 and IA-8 echo those of Tables 8 and 9 in that they show that the mean raw and factor-orthogonalized hedge returns to exploiting our set of 94 characteristics are zero after 2003 for big and small stocks, but positive for microcap stocks.

5. Conclusions and Implications

In this paper we have sought to respond to the challenge made by Cochrane (2011, p.1060) that researchers begin to identify which of the "veritable zoo" of hundreds of firm characteristics reported in prior studies as being statistically significant predictors of the cross-section of average stock returns. We use the same approach as Fama and French's seminal 1992 paper, but employ a far larger set of 94 firm characteristics and simultaneously include all 94 characteristics as explanatory variables in Fama-MacBeth regressions that seek to avoid overweighting microcaps and adjust for data snooping biases. Our approach leads us to estimate that 8-12 characteristics provide significant independent information about average U.S. monthly returns over the full period 1980-2014, with a far larger number of 82-86 characteristics being insignificant. Of the three characteristics-based versions of the low-dimensioned Carhart, five-factor and *q*-factor benchmark factor models over this same period, we find that the *q*-factor (2015) does best in capturing the multidimensionality that we observe in average returns.

We also document a striking shift in the number and economic importance of characteristics pre- versus post-2003, in that the number of independent characteristics and the hedge returns to exploiting them, drops suddenly, sharply and persistently in late 2002 / early 2003. Specifically, we find that just 1-2 characteristics are independent determinants of non-microcap returns after 2003 as compared to 11-16 characteristics before 2003, and that the mean hedge return to non-microcap stocks is insignificantly different from zero after 2003. We interpret the decline in the number and economic importance of the firm characteristics over calendar time and across firm size as consistent with the costly-limits-to-arbitrage market efficiency arguments of Shleifer and Vishny (1997) and others.

Our study also adds a third reason to those of Harvey, Liu and Zhou (2016) and McLean and Pontiff (2016) for why the hundreds of return anomalies reported in prior studies warrant skepticism—namely that that since 2003 almost no characteristics-based anomalies have existed in non-microcap stocks. Additionally, our pre- versus post-2003 results suggest that future empirical models of average returns could benefit from weighting post-2003 data more strongly (or even exclusively) relative to pre-2003 data, and from conditioning the return generating process on firm size. Lastly, since Green, Hand and Zhang (2013), Harvey, Liu and Zhu (2016) and Hou, Xue and Zhang (2016) all make readily available to researchers comprehensive libraries of anomaly variables—437 in the case of Hou, Xue and Zhang—future work could simultaneously evaluate an even larger number of firm characteristics than the 94 we assess, and shed more light on the substantial changes that have taken place in the process generating monthly U.S. stock returns, especially since 2003.

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APPENDIX

Acronym	Paper's author(s)	Date, Journal	Definition of the characteristic-based anomaly variable
absacc	Bandyopadhyay, Huang & Wirjanto	2010, WP	Absolute value of *acc*.
acc	Sloan	1996, TAR	Annual income before extraordinary items (*ib*) minus operating cash flows (*oancf*) divided by average total assets (*at*); if *oancf* is missing then set to change in *act* - change in *che* - change in *lct* + change in *dlc* + change in *txp-dp*.
aeavol	Lerman, Livnat & Mendenhall	2007, WP	Average daily trading volume (*vol*) for 3 days around earnings announcement minus average daily volume for 1-month ending 2 weeks before earnings announcement divided by 1-month average daily volume. Earnings announcement day from Compustat quarterly (*rdq*).
age	Jiang, Lee & Zhang	2005, RAS	Number of years since first Compustat coverage.
agr	Cooper, Gulen & Schill	2008, JF	Annual percent change in total assets (*at*).
baspread	Amihud & Mendelson	1989, JF	Monthly average of daily bid-ask spread divided by average of daily spread.
beta	Fama & MacBeth	1973, JPE	Estimated market beta from weekly returns and equal weighted market returns for 3 years ending month *t*-1 with at least 52 weeks of returns.
betasq	Fama & MacBeth	1973, JPE	Market beta squared.
bm	Rosenberg, Reid & Lanstein	1985, JPM	Book value of equity (*ceq*) divided by end of fiscal-year-end market capitalization.
bm_ia	Asness, Porter & Stevens	2000, WP	Industry adjusted book-to-market ratio.
cash	Palazzo	2012, JFE	Cash and cash equivalents divided by average total assets.
cashdebt	Ou & Penman	1989, JAE	Earnings before depreciation and extraordinary items (*ib+dp*) divided by avg. total liabilities (*lt*).
cashpr	Chandrashekar & Rao	2009, WP	Fiscal year end market capitalization plus long term debt (*dltt*) minus total assets (*at*) divided by cash and equivalents (*che*).
cfp	Desai, Rajgopal & Venkatachalam	2004, TAR	Operating cash flows divided by fiscal-year-end market capitalization.
cfp_ia	Asness, Porter & Stevens	2000, WP	Industry adjusted *cfp*.
chatoia	Soliman	2008, TAR	2-digit SIC - fiscal-year mean adjusted change in sales (*sale*) divided by average total assets (*at*).
chcsho	Pontiff & Woodgate	2008, JF	Annual percent change in shares outstanding (*csho*).
chempia	Asness, Porter & Stevens	1994, WP	Industry-adjusted change in number of employees.
chfeps	Hawkins, Chamberlin & Daniel	1984, FAJ	Mean analyst forecast in month prior to fiscal period end date from I/B/E/S summary file minus same mean forecast for prior fiscal period using annual earnings forecasts.
chinv	Thomas & Zhang	2002, RAS	Change in inventory (*inv*) scaled by average total assets (*at*).
chmom	Gettleman & Marks	2006, WP	Cumulative returns from months *t*-6 to *t*-1 minus months *t*-12 to *t*-7.
chnanalyst	Scherbina	2007, WP	Change in *nanalyst* from month *t*-3 to month *t*.
chpmia	Soliman	2008, TAR	2-digit SIC - fiscal-year mean adjusted change in income before extraordinary items (*ib*) divided by sales (*sale*).
chtx	Thomas & Zhang	2011, JAR	Percent change in total taxes (*txtq*) from quarter *t*-4 to *t*.

cinvest	Titman, Wei & Xie	2004, JFQA	Change over one quarter in net PP&E (*ppentq*) divided by sales (*saleq*) - average of this variable for prior 3 quarters; if *saleq* = 0, then scale by 0.01.
convind	Valta	2016, JFQA	An indicator equal to 1 if company has convertible debt obligations.
currat	Ou & Penman	1989, JAE	Current assets / current liabilities.
depr	Holthausen & Larcker	1992, JAE	Depreciation divided by PP&E.
disp	Diether, Malloy & Scherbina	2002, JF	Standard deviation of analyst 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 I/B/E/S summary files.
divi	Michaely, Thaler & Womack	1995, JF	An indicator variable equal to 1 if company pays dividends but did not in prior year.
divo	Michaely, Thaler & Womack	1995, JF	An indicator variable equal to 1 if company does not pay dividend but did in prior year.
dolvol	Chordia, Subrahmanyam & Anshuman	2001, JFE	Natural log of trading volume times price per share from month *t*-2.
dy	Litzenberger & Ramaswamy	1982, JF	Total dividends (*dvt*) divided by market capitalization at fiscal year-end.
ear	Kishore, Brandt, Santa-Clara & Venkatachalam	2008, WP	Sum of daily returns in three days around earnings announcement. Earnings announcement from Compustat quarterly file (*rdq*).
egr	Richardson, Sloan, Soliman & Tuna	2005, JAE	Annual percent change in book value of equity (*ceq*).
ep	Basu	1977, JF	Annual income before extraordinary items (*ib*) divided by end of fiscal year market cap.
fgr5yr	Bauman & Dowen	1988, FAJ	Most recently available analyst forecasted 5-year growth.
gma	Novy-Marx	2013, JFE	Revenues (*revt*) minus cost of goods sold (*cogs*) divided by lagged total assets (at).
grCAPX	Anderson & Garcia-Feijoo	2006, JF	Percent change in capital expenditures from year *t*-2 to year *t*.
grltnoa	Fairfield, Whisenant & Yohn	2003, TAR	Growth in long term net operating assets.
herf	Hou & Robinson	2006, JF	2-digit SIC - fiscal-year sales concentration (sum of squared percent of sales in industry for each company).
hire	Bazdresch, Belo & Lin	2014, JPE	Percent change in number of employees (*emp*).
idiovol	Ali, Hwang & Trombley	2003, JFE	Standard deviation of residuals of weekly returns on weekly equal weighted market returns for 3 years prior to month end.
ill	Amihud	2002, JFM	Average of daily (absolute return / dollar volume).
indmom	Moskowitz & Grinblatt	1999, JF	Equal weighted average industry 12-month returns.
invest	Chen & Zhang	2010, JF	Annual change in gross property, plant, and equipment (*ppegt*) + annual change in inventories (*invt*) all scaled by lagged total assets (*at*).
IPO	Loughran, Ritter & Ritter	1995, JF	An indicator variable equal to 1 if first year available on CRSP monthly stock file.
lev	Bhandari	1988, JF	Total liabilities (lt) divided by fiscal year end market capitalization.
lgr	Richardson, Sloan, Soliman & Tuna	2005, JAE	Annual percent change in total liabilities (*lt*).
maxret	Bali, Cakici & Whitelaw	2011, JFE	Maximum daily return from returns during calendar month *t*-1.
mom12m	Jegadeesh	1990, JF	11-month cumulative returns ending one month before month end.
mom1m	Jegadeesh & Titman	1993, JF	1-month cumulative return.
mom36m	Jegadeesh & Titman	1993, JF	Cumulative returns from months *t*-36 to *t*-13.

mom6m	Jegadeesh & Titman	1993, JF	5-month cumulative returns ending one month before month end.
ms	Mohanram	2005, RAS	Sum of 8 indicator variables for fundamental performance.
mve	Banz	1981, JFE	Natural log of market capitalization at end of month *t*-1.
mve_ia	Asness, Porter & Stevens	2000, WP	2-digit SIC industry-adjusted fiscal year-end market capitalization.
nanalyst	Elgers, Lo & Pfeiffer	2001, TAR	Number of analyst forecasts from most recently available I/B/E/S summary files in month prior to month of portfolio formation. *nanalyst* set to zero if not covered in I/B/E/S summary file.
nincr	Barth, Elliott & Finn	1999, JAR	Number of consecutive quarters (up to eight quarters) with an increase in earnings (*ibq*) over same quarter in the prior year.
operprof	Fama & French	2015, JFE	Revenue minus cost of goods sold - SG&A expense - interest expense divided by lagged common shareholders' equity.
orgcap	Eisfeldt & Papanikolaou	2013, JF	Capitalized SG&A expenses.
pchcapx_ia	Abarbanell & Bushee	1998, TAR	2-digit SIC - fiscal-year mean adjusted percent change in capital expenditures (*capx*).
pchcurrat	Ou & Penman	1989, JAE	Percent change in *currat*.
pchdepr	Holthausen & Larcker	1992, JAE	Percent change in *depr*.
pchgm_pchsale	Abarbanell & Bushee	1998, TAR	Percent change in gross margin (*sale*-*cogs*) minus percent change in sales (*sale*).
pchquick	Ou & Penman	1989, JAE	Percent change in *quick*.
pchsale_pchinvt	Abarbanell & Bushee	1998, TAR	Annual percent change in sales (*sale*) minus annual percent change in inventory (*invt*).
pchsale_pchrect	Abarbanell & Bushee	1998, TAR	Annual percent change in sales (*sale*) minus annual percent change in receivables (*rect*).
pchsale_pchxsga	Abarbanell & Bushee	1998, TAR	Annual percent change in sales (*sale*) minus annual percent change in SG&A (*xsga*).
pchsaleinv	Ou & Penman	1989, JAE	Percent change in *saleinv*.
pctacc	Hafzalla, Lundholm & Van Winkle	2011, TAR	Same as *acc* except that the numerator is divided by the absolute value of *ib*; if *ib* = 0 then *ib* set to 0.01 for denominator.
pricedelay	Hou & Moskowitz	2005, RFS	The 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.
ps	Piotroski	2000, JAR	Sum of 9 indicator variables to form fundamental health score.
quick	Ou & Penman	1989, JAE	(current assets - inventory) / current liabilities.
rd	Eberhart, Maxwell & Siddique	2004, JF	An indicator variable equal to 1 if R&D expense as a percentage of total assets has an increase greater than 5%.
rd_mve	Guo, Lev & Shi	2006, JBFA	R&D expense divided by end-of-fiscal-year market capitalization.
rd_sale	Guo, Lev & Shi	2006, JBFA	R&D expense divided by sales (*xrd*/*sale*).
realestate	Tuzel	2010, RFS	Buildings and capitalized leases divided by gross PP&E.
retvol	Ang, Hodrick, Xing & Zhang	2006, JF	Standard deviation of daily returns from month *t*-1.
roaq	Balakrishnan, Bartov & Faurel	2010, JAE	Income before extraordinary items (*ibq*) divided by one quarter lagged total assets (*atq*).

roavol	Francis, LaFond, Olsson & Schipper	2004, TAR	Standard deviaiton for 16 quarters of income before extraordinary items (*ibq*) divided by average total assets (*atq*).
roeq	Hou, Xue & Zhang	2014, RFS	Earnings before extraordinary items divided by lagged common shareholders' equity.
roic	Brown & Rowe	2007, WP	Annual earnings before interest and taxes (*ebit*) minus non-operating income (*nopi*) divided by non-cash enterprise value (*ceq*+*lt*-*che*).
rsup	Kama	2009, JBFA	Sales from quarter t minus sales from quarter *t*-4 (*saleq*) divided by fiscal-quarter-end market capitalization (*cshoq* * *prccq*).
salecash	Ou & Penman	1989, JAE	Annual sales divided by cash and cash equivalents.
saleinv	Ou & Penman	1989, JAE	Annual sales divided by total inventory.
salerec	Ou & Penman	1989, JAE	Annual sales divided by accounts receivable.
secured	Valta	2016, JFQA	Total liability scaled secured debt.
securedind	Valta	2016, JFQA	An indicator equal to 1 if company has secured debt obligations.
sfe	Elgers, Lo & Pfeiffer	2001, TAR	Analysts mean annual earnings forecast for nearest upcoming fiscal year from most recent month available prior to month of portfolio formation from I/B/E/S summary files scaled by price per share at fiscal quarter end.
sgr	Lakonishok, Shleifer & Vishny	1994, JF	Annual percent change in sales (*sale*).
sin	Hong & Kacperczyk	2009, JFE	An indicator variable equal to 1 if a company's primary industry classification is in smoke or tobacco, beer or alcohol, or gaming.
SP	Barbee, Mukherji, & Raines	1996, FAJ	Annual revenue (*sale*) divided by fiscal-year-end market capitalization.
std_dolvol	Chordia, Subrahmanyam & Anshuman	2001, JFE	Monthly standard deviation of daily dollar trading volume.
std_turn	Chordia, Subrahmanyam, &Anshuman	2001, JFE	Monthly standard deviation of daily share turnover.
stdacc	Bandyopadhyay, Huang & Wirjanto	2010, WP	Standard deviation for 16 quarters of accruals (*acc* measured with quarterly Compustat) scaled by sales; if *saleq* = 0, then scale by 0.01.
stdcf	Huang	2009, JEF	Standard deviation for 16 quarters of cash flows divided by sales (*saleq*); if *saleq* = 0, then scale by 0.01. Cash flows defined as *ibq* minus quarterly accruals.
sue	Rendelman, Jones & Latane	1982, JFE	Unexpected quarterly earnings divided by fiscal-quarter-end market cap. Unexpected earnings is I/B/E/S actual earnings minus median forecasted earnings if available, else it is the seasonally differenced quarterly earnings before extraordinary items from Compustat quarterly file.
tang	Almeida & Campello	2007, RFS	Cash holdings + 0.715 × receivables + 0.547 × inventory + 0.535 × PPE/ total assets.
tb	Lev & Nissim	2004, TAR	Tax income, calculated from current tax expense divided by maximum federal tax rate, divided by income before extraordinary items.
turn	Datar, Naik & Radcliffe	1998, JFM	Average monthly trading volume for most recent 3 months scaled by number of shares outstanding in current month.
zerotrade	Liu	2006, JFE	Turnover weighted number of zero trading days for most recent 1 month.

TABLE 1

Listing of firm characteristics used in the study. The source for and exact definition of each characteristic is in the Appendix.

Acronym	Firm characteristic	Acronym	Firm characteristic
absacc	Absolute accruals	*divo*	Dividend omission
acc	Working capital accruals	*dolvol*	Dollar trading volume
aeavol	Abnormal earnings announcement volume	*dy*	Dividend to price
age	# years since first Compustat coverage	*ear*	Earnings announcement return
agr	Asset growth	*egr*	Growth in common shareholder equity
baspread	Bid-ask spread	*ep*	Earnings to price
beta	Beta	*fgr5yr*	Forecasted growth in 5-year EPS
betasq	Beta squared	*gma*	Gross profitability
bm	Book-to-market	*grCAPX*	Growth in capital expenditures
bm_ia	Industry-adjusted book to market	*grltnoa*	Growth in long term net operating assets
cash	Cash holdings	*herf*	Industry sales concentration
cashdebt	Cash flow to debt	*hire*	Employee growth rate
cashpr	Cash productivity	*idiovol*	Idiosyncratic return volatility
cfp	Cash flow to price ratio	*ill*	Illiquidity
cfp_ia	Industry-adjusted cash flow to price ratio	*indmom*	Industry momentum
chatoia	Industry-adjusted change in asset turnover	*invest*	Capital expenditures and inventory
chcsho	Change in shares outstanding	*IPO*	New equity issue
chempia	Industry-adjusted change in employees	*lev*	Leverage
chfeps	Change in forecasted EPS	*lgr*	Growth in long-term debt
chinv	Change in inventory	*maxret*	Maximum daily return
chmom	Change in 6-month momentum	*mom12m*	12-month momentum
chnanalyst	Change in number of analysts	*mom1m*	1-month momentum
chpmia	Industry-adjusted change in profit margin	*mom36m*	36-month momentum
chtx	Change in tax expense	*mom6m*	6-month momentum
cinvest	Corporate investment	*ms*	Financial statement score
convind	Convertible debt indicator	*mve*	Size
currat	Current ratio	*mve_ia*	Industry-adjusted size
depr	Depreciation / PP&E	*nanalyst*	Number of analysts covering stock
disp	Dispersion in forecasted EPS	*nincr*	Number of earnings increases
divi	Dividend initiation	*operprof*	Operating profitability

TABLE 1 (continued)

Acronym	**Firm characteristic**	**Acronym**	**Firm characteristic**
orgcap	Organizational capital	*roeq*	Return on equity
pchcapx_ia	Industry adjusted % change in capital expenditures	*roic*	Return on invested capital
pchcurrat	% change in current ratio	*rsup*	Revenue surprise
pchdepr	% change in depreciation	*salecash*	Sales to cash
pchgm_pchsale	% change in gross margin - % change in sales	*saleinv*	Sales to inventory
pchquick	% change in quick ratio	*salerec*	Sales to receivables
pchsale_pchinvt	% change in sales - % change in inventory	*secured*	Secured debt
pchsale_pchrect	% change in sales - % change in A/R	*securedind*	Secured debt indicator
pchsale_pchxsga	% change in sales - % change in SG&A	*sfe*	Scaled earnings forecast
pchsaleinv	% change sales-to-inventory	*sgr*	Sales growth
pctacc	Percent accruals	*sin*	Sin stocks
pricedelay	Price delay	*SP*	Sales to price
ps	Financial statements score	*std_dolvol*	Volatility of liquidity (dollar trading volume)
quick	Quick ratio	*std_turn*	Volatility of liquidity (share turnover)
rd	R&D increase	*stdacc*	Accrual volatility
rd_mve	R&D to market capitalization	*stdcf*	Cash flow volatility
rd_sale	R&D to sales	*sue*	Unexpected quarterly earnings
realestate	Real estate holdings	*tang*	Debt capacity/firm tangibility
retvol	Return volatility	*tb*	Tax income to book income
roaq	Return on assets	*turn*	Share turnover
roavol	Earnings volatility	*zerotrade*	Zero trading days

TABLE 2

Available data and missing observations for firm characteristics

Firm characteristic	# obs.	% miss.	Firm characteristic	# obs.	% miss.	Firm characteristic	# obs.	% miss
absacc	1,662,391	14%	*egr*	1,801,782	7%	*pchsale_pchxsga*	1,499,205	22%
acc	1,662,391	14%	*ep*	1,933,898	0%	*pchsaleinv*	1,409,289	27%
aeavol	1,710,488	12%	*fgr5yr*	760,194	61%	*pctacc*	1,662,379	14%
age	1,933,898	0%	*gma*	1,797,401	7%	*pricedelay*	1,913,115	1%
agr	1,801,938	7%	*grcapx*	1,614,361	17%	*ps*	1,801,971	7%
baspread	1,933,853	0%	*grltnoa*	1,347,837	30%	*quick*	1,856,862	4%
beta	1,913,144	1%	*herf*	1,933,888	0%	*rd*	1,801,971	7%
betasq	1,913,144	1%	*hire*	1,797,477	7%	*rd_mve*	931,907	52%
bm	1,933,898	0%	*idiovol*	1,913,144	1%	*rd_sale*	918,493	53%
bm_ia	1,933,898	0%	*ill*	1,871,487	3%	*realestate*	800,058	59%
cash	1,712,248	11%	*indmom*	1,933,741	0%	*retvol*	1,933,841	0%
cashdebt	1,864,432	4%	*invest*	1,740,556	10%	*roaq*	1,720,520	11%
cashpr	1,913,829	1%	*ipo*	1,933,898	0%	*roavol*	1,453,242	25%
cfp	1,775,090	8%	*lev*	1,928,357	0%	*roeq*	1,720,115	11%
cfp_ia	1,775,090	8%	*lgr*	1,795,724	7%	*roic*	1,844,919	5%
chatoia	1,657,109	14%	*maxret*	1,933,897	0%	*rsup*	1,709,439	12%
chcsho	1,801,190	7%	*mom12m*	1,791,487	7%	*salecash*	1,917,657	1%
chempia	1,797,477	7%	*mom1m*	1,933,898	0%	*saleinv*	1,526,455	21%
chfeps	1,000,523	48%	*mom36m*	1,502,039	22%	*salerec*	1,865,648	4%
chinv	1,754,017	9%	*mom6m*	1,875,749	3%	*secured*	1,132,250	41%
chmom	1,791,487	7%	*ms*	1,723,698	11%	*securedind*	1,933,898	0%
chnanalyst	1,455,603	25%	*mve*	1,933,898	0%	*sfe*	988,655	49%
chpmia	1,774,849	8%	*mve_ia*	1,933,898	0%	*sgr*	1,778,807	8%
chtx	1,688,004	13%	*nanalyst*	1,480,584	23%	*sin*	1,933,898	0%
cinvest	1,684,236	13%	*nincr*	1,723,698	11%	*sp*	1,928,325	0%
convind	1,933,898	0%	*operprof*	1,797,245	7%	*std_dolvol*	1,868,232	3%
currat	1,866,803	3%	*orgcap*	1,422,289	26%	*std_turn*	1,873,288	3%
depr	1,849,276	4%	*pchcapx_ia*	1,751,021	9%	*stdacc*	1,213,569	37%
disp	825,468	57%	*pchcurrat*	1,732,739	10%	*stdcf*	1,213,569	37%
divi	1,801,971	7%	*pchdepr*	1,714,330	11%	*sue*	1,711,920	11%
divo	1,801,971	7%	*pchgm_pchsal*	1,778,662	8%	*tang*	1,853,308	4%
dolvol	1,860,698	4%	*pchquick*	1,721,978	11%	*tb*	1,703,039	12%
dy	1,928,742	0%	*pchsale_pchin*	1,427,946	26%	*turn*	1,861,339	4%
ear	1,722,142	11%	*pchsale_pchre*	1,727,611	11%	*zerotrade*	1,871,513	3%

This table shows the number of firm-month observations (# obs.) over Jan. 1980 – Dec. 2014 with sufficient data to calculate a given firm characteristic, and the percent of firm-months with missing observations (% miss). The sample is all common stocks on the NYSE, AMEX and NASDAQ exchanges with available annual and quarterly Compustat accounting data and CRSP stock return data. Analyst data is from I/B/E/S. Firm-month observations are created using monthly stock returns, including delisting returns, for each month t. Stock returns in month t are matched with the accounting data most recently available as of the end of month t-1, under the assumption that that annual accounting data are available at the end of month t-1 if the firm's fiscal year ended at least six months before the end of month t-1, and that quarterly accounting data are available at the end of month t-1 if the fiscal quarter ended at least four months before the end of month t-1.

TABLE 3

Descriptive statistics on the degree of cross-correlation among firm characteristics

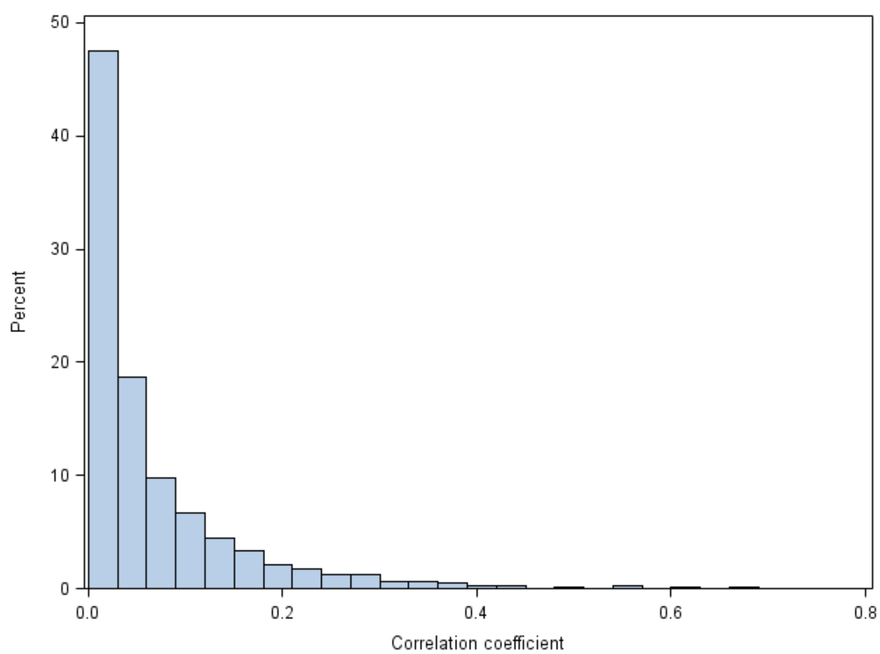
Panel A: Variance inflation factors (VIFs)

	# characteristics	Min.	10th pct.	Median	Mean	90th pct.	Max.
Before removing VIF > 7	102	1	1.1	1.8	3.8	9.8	22.1
After removing VIF > 7	94	1	1.1	1.6	2.1	3.9	6.9

Panel B: Absolute cross-correlations

	# characteristics	Min.	10th pct.	Median	Mean	90th pct.	Max.
Before removing VIF > 7	102	0	0.004	0.03	0.07	0.18	0.95
After removing VIF > 7	94	0	0.004	0.03	0.07	0.18	0.77

Panel C: Distribution of the absolute cross-correlations among characteristics after removal of characteristics with VIFs>7



This table presents descriptive statistics on the degree of cross-correlation among firm characteristics. Panel A shows statistics from the distribution of variance inflation factors (VIFs) where the VIF for each characteristic is calculated as $1/(1-R^2)$ with R^2 being the that from regressing each characteristic on all the other characteristics in a pooled regression. After examining the VIFs we remove 8 characteristics with high VIFs such that the resulting maximum VIF ≤ 7. The characteristics removed are *betasq*, *dolvol*, *maxret*, *mom6m*, *pchquick*, *quick*, *stdacc*, and *lgr*. Panel B describes the distribution of the absolute value of Pearson correlations between all pairs of characteristics using the pooled sample of firm-month observations. Panel C graphs the distribution of the absolute cross-correlations after the 8 cross-correlated characteristics with large VIFs are removed.

TABLE 4

Results of Fama-MacBeth (FM) regressions of monthly stock returns on the firm characteristics versions of notable benchmark factor models. *t*-statistics with an absolute value ≥ 3.0 (1.96) are boxed and in bold (not boxed and in bold).

	Set of stocks, regression method					
	Column A: All stocks, value-weighted WLS		Column B: All-but-microcap stocks, OLS		Column C: All stocks, OLS	
	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.
Panel A: Carhart (1997) model						
mve	-0.09	-1.0	-0.05	-1.0	-0.26	**-2.4**
bm	0.12	0.8	0.12	1.7	0.22	$\boxed{\mathbf{3.0}}$
mom12m	0.26	**2.2**	0.21	**2.0**	0.25	**2.7**
Mean # obs.	4,605		1,835		4,605	
Mean adj. R^2	6.3%		3.6%		2.0%	
Panel B: Fama-French (2015) five-factor model						
mve	-0.09	-0.9	-0.05	-1.0	-0.16	-1.5
bm	0.14	0.9	0.10	1.4	0.21	**2.7**
agr	-0.19	$\boxed{\mathbf{-3.1}}$	-0.25	$\boxed{\mathbf{-5.0}}$	-0.37	$\boxed{\mathbf{-8.4}}$
operprof	0.14	$\boxed{\mathbf{3.1}}$	0.11	$\boxed{\mathbf{3.4}}$	0.12	$\boxed{\mathbf{3.3}}$
Mean # obs.	4,605		1,835		4,605	
Mean adj. R^2	4.7%		2.6%		1.6%	
Panel C: Hou, Xue and Zhang (2015) q-factor model						
mve	-0.14	-1.4	-0.08	-1.5	-0.26	**-2.7**
agr	-0.21	$\boxed{\mathbf{-3.2}}$	-0.26	$\boxed{\mathbf{-4.9}}$	-0.39	$\boxed{\mathbf{-8.5}}$
roeq	0.20	$\boxed{\mathbf{3.1}}$	0.15	**2.9**	0.27	$\boxed{\mathbf{3.8}}$
Mean # obs.	4,605		1,835		4,605	
Mean adj. R^2	3.4%		1.9%		1.5%	

This table presents the results of monthly cross-sectional Fama-MacBeth (1973) regressions of stock returns in month t on benchmark characteristics as of the end of month t-1, using the characteristics representation the benchmark factor models of Carhart (1997), Fama and French (2015) and Hou, Xue and Zhang (2015). Three sets of regressions are shown for each benchmark model: Regressions using all stocks and WLS where the weight is the market value of equity for stock i at time t-1 (all stocks, value-weighted WLS), regressions using all-but-microcap stocks and OLS (all-but microcap stocks, OLS), and regressions using all stocks and OLS (all stocks, OLS). Microcap stocks are defined as those in month t-1 that have a market value of equity less than the 20th percentile of stocks on the NYSE stock exchange in month t-1. FM coefficients are the means of the monthly estimated coefficients*100; *t*-statistics are taken the time series of monthly coefficient estimates and employ Newey-West adjustments of 12 lags. The sample is all common stocks on the NYSE, AMEX and NASDAQ exchanges with available annual and quarterly Compustat accounting data and CRSP stock return data. Analyst data is from I/B/E/S. Firm-month observations are created using monthly stock returns, including delisting returns, for each month t. Stock returns in month t are matched with the accounting data most recently available as of the end of month t-1, under the assumption that that annual accounting data are available at the end of month t-1 if the firm's fiscal year ended at least six months before the end of month t-1, and that quarterly accounting data are available at the end of month t-1 if the fiscal quarter ended at least four months before the end of month t-1. Intercepts are estimated but not reported.

TABLE 5

Fama-MacBeth (FM) regressions of monthly stock returns on each of the 94 firm characteristics studied one at a time, controlling either for no other characteristics (column A) or for the characteristics versions of notable benchmark factor models (columns B-D). *t*-statistics with an absolute value ≥ 3.0 (1.96) are boxed and in bold (not boxed and in bold).

	Column A: Single characteristic, No benchmark model controls						Column B: Single characteristic, Carhart benchmark model controls						Column C: Single characteristic, 5-factor benchmark model controls						Column D: Single characteristic, q-factor benchmark model controls					
	All stocks, VWLS		All-but-microcap, OLS		All stocks, OLS		All stocks, VWLS		All-but-microcap, OLS		All stocks, OLS		All stocks, VWLS		All-but-microcap, OLS		All stocks, OLS		All stocks, VWLS		All-but-microcap, OLS		All stocks, OLS	
	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.
# |*t*-stats| ≥ 3.0		4		17		35		15		25		35		8		8		26		3		5		22
# |*t*-stats| ≥ 1.96		26		39		49		32		46		53		25		28		43		19		21		39
agr	-0.22	**-3.1**	-0.27	**-4.6**	-0.44	**-8.1**	-0.20	**-3.4**	-0.25	**-5.1**	-0.37	**-8.3**												
bm	0.17	1.1	0.14	1.8	0.32	**4.8**													0.10	0.8	0.08	1.2	0.13	2.0
mom12m	0.31	**2.4**	0.21	1.9	0.22	**2.2**							0.27	**2.2**	0.20	1.9	0.23	**2.5**	0.28	**2.2**	0.20	1.9	0.27	**2.9**
mve	-0.10	-1.0	-0.05	-1.0	-0.25	**-2.3**																		
operprof	0.08	1.5	0.06	**2.1**	0.06	1.5	0.11	**2.4**	0.09	**2.9**	0.07	1.9							0.09	1.9	0.07	**2.4**	0.08	**2.6**
roeq	0.19	**2.4**	0.15	**2.5**	0.21	**2.4**	0.21	**3.0**	0.14	**3.0**	0.21	**3.2**	0.20	**3.2**	0.15	**3.2**	0.27	**4.0**						
absacc	-0.06	-0.5	-0.08	-1.4	-0.07	-0.8	-0.10	-1.1	-0.09	-1.9	-0.09	-1.5	-0.03	-0.3	-0.05	-1.0	-0.08	-1.3	0.00	0.0	-0.03	-0.7	-0.05	-0.9
acc	-0.21	**-2.4**	-0.12	**-2.5**	-0.17	**-2.6**	-0.13	-1.9	-0.09	**-2.3**	-0.13	**-2.4**	-0.18	**-2.4**	-0.09	**-2.1**	-0.08	-1.5	-0.19	**-2.4**	-0.10	**-2.4**	-0.14	**-3.1**
aeavol	0.02	0.3	0.00	0.0	0.09	**4.8**	-0.02	-0.5	-0.01	-0.6	0.05	**2.8**	0.01	0.1	0.00	0.1	0.07	**4.4**	0.01	0.2	0.00	0.2	0.07	**3.8**
age	0.02	0.2	0.08	1.2	0.13	1.8	0.09	1.2	0.09	1.9	0.18	**3.8**	-0.03	-0.3	-0.01	-0.2	0.10	**2.0**	-0.03	-0.3	0.01	0.1	0.06	1.0
baspread	-0.42	-1.2	-0.20	-1.5	0.10	0.6	-0.62	**-2.2**	-0.26	**-2.3**	0.01	0.1	-0.39	-1.3	-0.16	-1.3	0.01	0.0	-0.50	-1.3	-0.14	-1.1	-0.03	-0.2
beta	-0.07	-0.4	-0.11	-0.7	-0.12	-0.8	-0.17	-1.1	-0.15	-1.2	-0.08	-0.6	-0.03	-0.2	-0.05	-0.4	-0.04	-0.3	-0.04	-0.2	-0.04	-0.3	-0.03	-0.2
betasq	-0.08	-0.4	-0.12	-0.8	-0.13	-0.9	-0.20	-1.1	-0.17	-1.3	-0.11	-0.9	-0.04	-0.2	-0.07	-0.5	-0.06	-0.5	-0.04	-0.2	-0.06	-0.5	-0.04	-0.3
bm_ia	0.04	0.8	0.00	-0.1	0.01	0.2	0.03	0.7	0.01	0.2	0.02	0.3	0.04	0.9	0.01	0.3	0.02	0.5	0.05	1.1	0.01	0.2	0.01	0.1
cash	0.12	1.2	0.04	0.4	0.11	1.0	0.11	1.5	0.05	0.6	0.15	1.6	0.18	**2.0**	0.11	1.1	0.20	**2.1**	0.17	1.7	0.09	0.9	0.17	1.7
cashdebt	0.24	**2.1**	0.09	**2.0**	0.06	0.8	0.24	**2.4**	0.11	**3.1**	0.07	1.1	0.25	**2.6**	0.10	**2.8**	0.08	1.6	0.19	1.3	0.06	1.4	0.03	0.5
cashpr	-0.08	-1.7	-0.10	**-2.3**	-0.14	**-3.2**	-0.03	-0.8	-0.04	-1.4	-0.01	-0.5	-0.06	-1.6	-0.06	-1.9	-0.02	-0.6	-0.06	-1.5	-0.06	-1.8	-0.06	-1.3
cfp	0.12	1.2	0.12	1.8	0.13	1.7	0.16	1.0	0.13	**2.8**	0.16	**2.3**	0.14	0.8	0.11	**2.2**	0.22	**2.8**	0.04	0.2	0.08	1.4	0.20	**2.7**
cfp_ia	-0.01	-0.2	0.00	0.1	0.04	1.0	-0.02	-0.4	0.02	0.5	0.03	0.9	0.00	0.0	0.02	0.5	0.03	0.9	0.00	0.0	0.01	0.3	0.03	0.8

chatoia	0.08	1.7	0.08	**4.0**	0.09	**5.1**	0.06	1.5	0.07	**3.6**	0.08	**4.5**	0.02	0.6	0.04	**2.0**	0.05	**2.9**	0.02	0.5	0.04	1.9	0.04	**2.1**
chcsho	-0.13	**-2.9**	-0.17	**-3.4**	-0.27	**-6.5**	-0.10	**-2.9**	-0.14	**-3.5**	-0.20	**-5.9**	-0.07	**-2.4**	-0.06	**-2.1**	-0.11	**-3.3**	-0.09	**-2.7**	-0.07	**-2.5**	-0.09	**-3.1**
chempia	-0.02	-0.5	-0.06	-1.3	-0.16	**-4.1**	-0.01	-0.2	-0.05	-1.2	-0.12	**-3.4**	0.07	1.5	0.05	1.6	0.01	0.2	0.06	1.3	0.05	1.6	0.01	0.3
chfeps	0.13	**2.3**	0.10	**2.4**	0.20	**5.8**	0.06	1.3	0.09	**2.5**	0.17	**5.5**	0.12	**2.3**	0.10	**2.6**	0.19	**5.7**	0.12	**2.2**	0.10	**2.7**	0.20	**5.8**
chinv	-0.16	**-3.2**	-0.14	**-4.3**	-0.25	**-6.5**	-0.11	**-2.9**	-0.12	**-4.4**	-0.20	**-5.7**	-0.10	**-2.4**	-0.08	**-2.8**	-0.11	**-3.6**	-0.09	**-2.0**	-0.07	**-2.6**	-0.13	**-4.3**
chmom	-0.31	**-3.0**	-0.12	-1.9	-0.21	**-3.5**	-0.28	**-3.2**	-0.10	-1.8	-0.17	**-3.0**	-0.32	**-3.6**	-0.12	**-2.3**	-0.21	**-3.9**	-0.32	**-3.4**	-0.11	**-2.0**	-0.16	**-2.8**
chnanalyst	0.00	0.0	-0.08	**-2.2**	-0.06	-1.8	-0.01	-0.5	-0.07	**-2.9**	-0.04	-1.7	0.00	-0.1	-0.05	-1.9	-0.01	-0.5	0.00	-0.2	-0.05	-1.8	-0.02	-0.8
chpmia	0.01	0.2	0.01	0.2	0.02	0.5	0.00	0.0	0.00	0.0	0.02	0.5	0.00	0.1	0.00	0.1	0.02	0.7	0.01	0.2	0.01	0.3	0.01	0.4
chtx	0.09	1.7	0.06	1.8	0.14	**5.2**	0.04	1.0	0.02	0.7	0.09	**4.0**	0.12	**3.3**	0.10	**3.5**	0.18	**6.9**	0.09	**2.1**	0.06	**2.1**	0.14	**5.8**
cinvest	0.02	0.5	-0.03	-1.2	0.01	0.6	0.01	0.2	-0.03	-1.3	0.02	1.0	0.00	0.0	-0.04	-1.5	0.00	-0.1	-0.01	-0.2	-0.05	**-2.0**	-0.01	-0.8
convind	-0.17	-1.7	-0.13	-1.4	-0.39	**-4.0**	-0.15	-1.7	-0.10	-1.1	-0.29	**-3.0**	-0.11	-1.3	-0.08	-0.9	-0.29	**-2.7**	-0.09	-1.1	-0.04	-0.5	-0.20	**-2.0**
currat	-0.10	-1.5	-0.10	**-2.2**	-0.03	-0.8	-0.07	-1.4	-0.06	-1.8	-0.02	-0.7	-0.05	-1.0	-0.03	-1.0	0.02	0.6	-0.09	-1.3	-0.05	-1.2	-0.04	-1.5
depr	0.02	0.2	0.01	0.1	0.11	1.5	0.01	0.1	0.02	0.4	0.09	1.6	0.04	0.4	0.03	0.7	0.07	1.2	0.06	0.7	0.04	0.8	0.07	1.2
disp	-0.15	-1.4	-0.08	-1.4	-0.16	**-2.6**	-0.15	-1.7	-0.09	-1.9	-0.16	**-3.4**	-0.11	-1.2	-0.07	-1.3	-0.17	**-3.4**	-0.10	-1.1	-0.06	-1.1	-0.16	**-3.3**
divi	-0.13	-0.7	-0.31	**-2.0**	-0.33	**-2.6**	-0.23	-1.3	-0.34	**-2.7**	-0.42	**-4.0**	-0.15	-0.9	-0.16	-1.3	-0.27	**-2.6**	-0.15	-0.8	-0.20	-1.4	-0.26	**-2.4**
divo	0.14	0.7	-0.14	-0.8	0.00	0.0	-0.08	-0.5	-0.21	-1.5	-0.10	-1.1	0.16	0.9	-0.04	-0.3	-0.05	-0.5	0.16	0.9	-0.08	-0.6	-0.06	-0.7
dolvol	-0.16	-1.3	-0.08	-1.3	-0.23	**-2.8**	-0.20	-0.8	-0.12	-0.9	0.04	0.2	0.04	0.1	0.03	0.2	0.25	1.0	0.04	0.1	0.04	0.3	0.25	1.0
dy	0.03	0.2	0.05	0.7	0.03	0.5	0.01	0.2	0.02	0.3	0.03	0.6	-0.05	-0.5	-0.03	-0.4	-0.01	-0.2	-0.02	-0.2	-0.01	-0.1	-0.02	-0.4
ear	0.13	**2.2**	0.11	**5.0**	0.19	**7.2**	0.06	1.5	0.07	**4.4**	0.13	**6.2**	0.12	**2.2**	0.09	**4.3**	0.17	**7.1**	0.12	**2.1**	0.09	**4.0**	0.15	**6.3**
egr	-0.19	**-2.8**	-0.19	**-3.9**	-0.22	**-4.8**	-0.18	**-3.1**	-0.18	**-4.3**	-0.18	**-4.7**	-0.10	**-2.1**	-0.08	**-2.7**	-0.02	-0.9	-0.07	-1.7	-0.05	**-2.0**	-0.01	-0.5
ep	0.22	1.0	0.07	0.9	0.01	0.1	0.25	1.6	0.07	1.2	0.07	0.8	0.19	1.2	0.07	1.0	0.14	1.5	0.14	0.7	0.03	0.5	0.08	0.9
fgr5yr	0.00	0.0	-0.08	-0.5	-0.05	-0.4	-0.12	-0.6	-0.12	-0.9	-0.10	-0.8	0.08	0.3	0.02	0.1	0.04	0.3	0.06	0.3	0.01	0.1	0.03	0.3
gma	0.09	1.1	0.05	1.1	0.07	1.7	0.16	**2.5**	0.09	**2.4**	0.10	**2.3**	0.19	**2.4**	0.12	**2.4**	0.20	**5.1**	0.13	1.7	0.08	1.8	0.14	**3.4**
grcapx	-0.17	**-2.8**	-0.15	**-4.2**	-0.21	**-7.4**	-0.17	**-3.2**	-0.14	**-4.2**	-0.19	**-7.5**	-0.10	**-2.5**	-0.08	**-3.1**	-0.11	**-4.7**	-0.10	**-2.4**	-0.08	**-3.0**	-0.10	**-4.4**
grltnoa	-0.18	**-4.0**	-0.20	**-4.5**	-0.33	**-6.7**	-0.16	**-3.9**	-0.17	**-4.5**	-0.27	**-6.2**	-0.07	-1.5	-0.06	-1.6	-0.11	**-2.9**	-0.06	-1.2	-0.06	-1.5	-0.10	**-2.6**
herf	0.03	1.0	0.00	0.0	-0.05	-1.4	0.04	1.3	0.00	0.0	-0.08	**-2.4**	0.04	1.3	0.00	0.1	-0.08	**-2.2**	0.04	1.3	0.00	0.0	-0.06	-1.5
hire	-0.13	**-2.0**	-0.17	**-3.2**	-0.30	**-7.2**	-0.12	**-2.4**	-0.15	**-3.4**	-0.25	**-7.1**	0.01	0.2	0.00	-0.1	-0.08	**-3.3**	0.01	0.3	-0.01	-0.2	-0.07	**-2.5**
idiovol	-0.12	-0.5	-0.17	-1.2	-0.06	-0.4	-0.34	-1.5	-0.25	**-2.0**	-0.24	-1.6	-0.07	-0.3	-0.12	-0.9	-0.18	-1.2	-0.04	-0.2	-0.09	-0.7	-0.14	-0.9
ill	-0.14	-1.1	-0.06	**-2.7**	0.33	**4.4**	-0.21	-1.9	-0.05	**-2.2**	0.27	**4.6**	-0.34	**-3.0**	-0.08	**-3.1**	0.22	**3.8**	-0.34	**-3.0**	-0.09	**-3.4**	0.20	**3.3**
indmom	0.07	1.1	0.15	1.6	0.35	**3.8**	0.01	0.2	0.09	1.4	0.29	**4.0**	0.05	0.9	0.13	1.6	0.32	**3.8**	0.05	0.8	0.12	1.4	0.30	**3.5**
invest	-0.14	**-2.7**	-0.20	**-4.2**	-0.36	**-7.0**	-0.13	**-3.3**	-0.18	**-4.5**	-0.30	**-7.1**	-0.06	-1.0	-0.07	-1.8	-0.15	**-3.3**	-0.05	-0.8	-0.07	-1.8	-0.16	**-3.5**

ipo	-0.10	-0.5	-0.30	-1.2	-0.73	**-4.5**	0.00	**5.7**	0.00	**5.7**	0.00	**5.7**	-0.15	-0.7	0.13	0.6	-0.52	**-2.5**	-0.06	-0.3	0.26	1.0	-0.35	-1.7
lev	0.04	0.4	0.08	1.0	0.05	0.6	-0.01	-0.1	0.01	0.1	-0.07	-0.9	0.01	0.1	0.02	0.3	-0.07	-0.8	0.02	0.2	0.04	0.5	-0.04	-0.5
lgr	-0.18	**-2.9**	-0.17	**-4.2**	-0.31	**-8.8**	-0.16	**-3.3**	-0.15	**-5.0**	-0.27	**-9.7**	0.06	1.4	0.06	1.8	-0.05	-1.4	0.07	1.4	0.06	1.7	0.00	-0.1
maxret	-0.22	-1.1	-0.23	**-2.1**	-0.29	**-2.4**	-0.38	**-2.3**	-0.27	**-3.2**	-0.41	**-4.2**	-0.24	-1.4	-0.21	**-2.2**	-0.41	**-4.2**	-0.22	-1.2	-0.19	**-2.0**	-0.43	**-4.4**
mom1m	-0.12	-1.1	-0.13	-1.9	-0.58	**-6.2**	-0.28	**-3.1**	-0.23	**-3.5**	-0.67	**-7.7**	-0.25	**-2.5**	-0.21	**-2.8**	-0.65	**-7.3**	-0.22	**-2.1**	-0.19	**-2.6**	-0.63	**-7.1**
mom36m	-0.07	-0.8	-0.15	**-2.3**	-0.22	**-2.5**	-0.11	-1.3	-0.14	**-2.3**	-0.14	-1.9	-0.06	-0.7	-0.09	-1.6	-0.08	-1.1	-0.08	-1.0	-0.11	**-2.0**	-0.11	-1.8
mom6m	0.08	0.7	0.15	1.6	0.13	1.5	-0.32	**-2.7**	-0.06	-0.8	-0.08	-1.1	0.05	0.5	0.12	1.4	0.12	1.6	0.04	0.4	0.12	1.3	0.18	**2.3**
ms	0.03	0.9	0.05	1.6	0.04	0.9	0.08	**2.7**	0.08	**3.2**	0.12	**4.8**	0.07	**2.1**	0.07	**2.6**	0.12	**4.9**	0.05	1.3	0.05	1.6	0.09	**3.4**
mve_ia	-0.02	-1.1	-0.05	-1.3	-0.04	-0.8	0.01	0.4	0.03	1.0	0.15	**3.9**	-0.03	-1.4	-0.03	-0.6	0.08	2.0	-0.03	-1.4	-0.02	-0.4	0.07	2.0
nanalyst	-0.02	-0.3	-0.04	-0.8	-0.08	-1.1	0.02	0.5	0.05	0.8	0.43	**4.1**	0.02	0.5	0.04	0.6	0.36	**3.2**	0.02	0.4	0.05	0.7	0.31	**3.0**
nincr	0.07	**2.6**	0.08	**3.5**	0.13	**6.0**	0.06	**2.9**	0.06	**3.5**	0.11	**6.1**	0.08	**3.6**	0.09	**4.7**	0.15	**8.2**	0.06	**2.8**	0.07	**3.6**	0.11	**6.1**
orgcap	0.17	**2.0**	0.11	**2.1**	0.24	**3.1**	0.22	**2.6**	0.12	**2.6**	0.19	**3.0**	0.08	1.0	0.05	1.0	0.13	1.8	0.11	1.4	0.07	1.4	0.17	**2.6**
pchcapx_ia	0.02	0.5	0.00	-0.1	0.00	-0.1	0.02	0.5	0.00	0.1	0.00	0.1	0.03	0.9	0.02	0.5	0.02	0.4	0.04	1.1	0.01	0.4	0.03	0.7
pchcurrat	-0.11	**-2.9**	-0.08	**-3.4**	-0.07	**-2.5**	-0.10	**-3.2**	-0.08	**-3.7**	-0.07	**-2.4**	-0.07	**-2.2**	-0.02	-1.2	0.00	0.0	-0.08	**-2.5**	-0.03	-1.5	-0.04	-1.7
pchdepr	0.03	0.6	0.02	0.6	-0.01	-0.2	-0.01	-0.1	0.01	0.3	-0.03	-0.8	0.05	1.0	0.01	0.4	-0.06	-1.9	0.05	1.0	0.01	0.5	-0.03	-1.0
pchgm_pchsale	0.08	**2.4**	0.07	**2.8**	0.11	**3.6**	0.07	**2.6**	0.07	**3.1**	0.10	**4.4**	0.04	1.4	0.05	**2.3**	0.08	**3.3**	0.03	1.0	0.04	1.8	0.06	**2.5**
pchquick	-0.06	-1.7	-0.05	**-2.1**	-0.05	-1.9	-0.07	**-2.0**	-0.05	**-2.6**	-0.05	-1.8	-0.03	-0.9	0.00	0.3	0.02	0.7	-0.04	-1.2	0.00	-0.1	-0.01	-0.6
pchsale_pchinvt	0.07	1.6	0.09	**3.7**	0.14	**5.3**	0.05	1.4	0.08	**4.3**	0.13	**5.0**	0.03	0.9	0.06	**2.8**	0.09	**3.6**	0.03	0.7	0.05	**2.0**	0.08	**3.1**
pchsale_pchrect	0.02	0.6	0.04	1.8	0.09	**4.7**	0.02	0.5	0.03	1.5	0.09	**4.9**	-0.02	-0.6	-0.03	-1.3	0.02	0.9	-0.02	-0.5	-0.02	-1.2	0.01	0.4
pchsale_pchxsga	-0.09	-1.7	-0.09	**-3.0**	-0.09	**-3.3**	-0.09	-1.7	-0.08	**-3.1**	-0.07	**-2.8**	-0.02	-0.4	-0.03	-1.5	0.00	-0.2	-0.04	-0.8	-0.05	**-2.0**	-0.01	-0.4
pchsaleinv	0.05	1.0	0.05	2.0	0.05	1.6	0.03	0.6	0.04	1.8	0.04	1.6	0.04	0.8	0.05	1.8	0.04	1.5	0.02	0.5	0.04	1.5	0.02	0.4
pctacc	-0.03	-0.6	-0.04	**-2.0**	-0.11	**-4.0**	-0.01	-0.2	-0.03	-1.6	-0.09	**-4.3**	0.00	-0.1	-0.02	-1.1	-0.08	**-3.7**	-0.02	-0.5	-0.02	-1.2	-0.08	**-3.2**
pricedelay	0.04	0.5	0.01	0.3	0.03	1.3	0.03	0.5	0.02	1.0	0.00	0.0	0.05	0.7	0.02	0.7	0.00	-0.1	0.05	0.7	0.01	0.3	-0.01	-0.3
ps	0.04	1.4	0.07	**2.4**	0.08	**2.1**	0.03	1.4	0.07	**2.8**	0.11	**4.2**	0.02	0.9	0.05	**2.0**	0.10	**3.9**	0.01	0.4	0.04	1.6	0.07	**3.0**
quick	-0.11	-1.8	-0.09	-1.8	-0.02	-0.6	-0.09	-1.9	-0.06	-1.7	0.00	-0.1	-0.04	-0.8	-0.01	-0.3	0.05	1.5	-0.09	-1.5	-0.03	-0.8	-0.01	-0.3
rd	0.10	1.2	0.17	1.2	0.43	**2.0**	0.09	1.1	0.16	1.5	0.42	**2.4**	0.02	0.2	0.10	0.8	0.28	1.6	0.02	0.2	0.11	0.8	0.27	1.5
rd_mve	0.29	1.8	0.20	**2.1**	0.42	**3.5**	0.18	1.4	0.14	1.6	0.31	**2.9**	0.18	1.0	0.13	1.3	0.26	**2.5**	0.20	1.3	0.17	1.7	0.28	**2.7**
rd_sale	-0.04	-0.3	-0.08	-1.2	-0.02	-0.2	-0.01	-0.1	-0.07	-1.1	0.03	0.4	0.06	0.5	-0.02	-0.3	0.04	0.6	0.14	0.7	0.05	0.6	0.13	1.1
realestate	0.11	1.3	0.09	1.2	0.01	0.2	0.12	1.9	0.09	1.5	0.03	0.5	0.08	1.4	0.05	0.9	0.00	0.1	0.10	1.5	0.06	1.0	0.01	0.1
retvol	-0.26	-1.1	-0.25	**-2.0**	-0.17	-1.3	-0.45	**-2.3**	-0.31	**-3.1**	-0.30	**-2.7**	-0.26	-1.2	-0.22	**-2.0**	-0.29	**-2.5**	-0.24	-1.1	-0.20	-1.8	-0.32	**-2.8**
roaq	0.27	**2.5**	0.15	**2.1**	0.20	1.8	0.31	**3.9**	0.15	**3.0**	0.21	**2.4**	0.31	**3.8**	0.17	**3.2**	0.28	**3.2**	0.20	1.8	0.07	1.1	0.16	1.8

roavol	-0.06	-0.6	-0.08	-1.0	-0.06	-0.5	-0.13	-1.5	-0.09	-1.4	-0.10	-1.1	-0.03	-0.3	-0.05	-0.6	-0.09	-0.9	-0.02	-0.2	-0.04	-0.5	-0.05	-0.5
roic	0.33	**2.9**	0.13	**2.0**	0.04	0.4	0.37	**4.2**	0.14	**2.7**	0.05	0.6	0.34	**4.1**	0.12	**2.2**	0.07	0.9	0.33	**3.0**	0.07	1.3	0.01	0.2
rsup	0.03	0.4	0.04	0.9	-0.01	-0.2	0.00	0.0	0.02	0.6	-0.01	-0.2	0.06	0.8	0.07	**2.0**	0.08	1.8	0.06	0.8	0.07	1.8	0.05	1.2
salecash	0.05	0.9	0.02	0.7	0.01	0.4	0.02	0.4	0.02	0.8	-0.02	-0.6	0.00	-0.1	0.00	-0.2	-0.05	-1.5	0.00	0.1	0.00	0.0	-0.03	-1.0
saleinv	-0.01	-0.3	0.02	0.8	0.03	1.3	-0.02	-0.7	0.01	0.6	0.03	1.4	-0.01	-0.5	0.02	0.7	0.04	1.7	-0.01	-0.5	0.02	0.7	0.03	1.4
salerec	0.08	1.7	0.06	1.4	0.03	0.9	0.08	1.9	0.06	1.5	0.03	0.9	0.04	1.1	0.03	0.7	0.00	0.0	0.07	1.6	0.04	1.1	0.02	0.5
secured	0.03	0.3	-0.09	-1.3	0.03	0.5	0.05	0.6	-0.04	-1.1	-0.09	-1.7	0.07	1.0	0.08	0.9	-0.03	-0.6	0.04	0.4	-0.09	-0.9	-0.02	-0.3
securedind	0.11	0.9	0.05	0.4	0.06	0.4	0.15	1.0	0.10	0.8	0.01	0.1	0.10	0.9	0.09	0.9	0.03	0.2	0.16	1.1	0.13	1.1	0.12	0.9
sfe	-0.24	-1.3	-0.05	-0.8	0.06	0.6	-0.13	-0.9	-0.06	-1.0	0.07	0.8	-0.24	-1.5	-0.08	-1.4	0.09	1.0	-0.24	-1.3	-0.09	-1.4	0.08	1.0
sgr	-0.26	**-2.8**	-0.16	**-3.0**	-0.25	**-6.6**	-0.24	**-3.3**	-0.16	**-3.6**	-0.20	**-6.3**	-0.09	-1.5	-0.03	-0.8	-0.07	**-2.1**	-0.11	-1.6	-0.03	-0.7	-0.07	-1.9
sin	0.42	1.8	0.32	1.7	0.38	**2.0**	0.44	**2.2**	0.33	**2.0**	0.52	**2.9**	0.34	1.7	0.35	**2.1**	0.51	**2.8**	0.40	**2.0**	0.37	**2.2**	0.48	**2.5**
sp	0.26	1.7	0.15	**2.2**	0.23	**3.3**	0.08	0.9	0.08	1.5	0.03	0.5	-0.01	-0.1	0.03	0.6	-0.02	-0.3	0.13	1.1	0.09	1.5	0.08	1.2
std_dolvol	0.06	0.6	0.06	1.8	0.13	**2.3**	-0.09	-1.0	0.05	1.6	-0.07	-1.0	-0.09	-1.0	0.03	0.9	-0.10	-1.2	-0.08	-0.9	0.03	0.8	-0.09	-1.1
std_turn	0.00	0.0	-0.04	-0.5	-0.05	-0.8	-0.13	-1.5	-0.08	-1.4	-0.09	-1.6	0.01	0.1	-0.01	-0.1	-0.01	-0.2	0.01	0.1	0.00	0.0	0.00	0.0
stdacc	-0.10	**-2.3**	-0.07	-1.8	-0.09	-1.9	-0.13	**-4.3**	-0.08	**-2.9**	-0.10	**-2.9**	-0.08	**-2.6**	-0.05	-1.6	-0.08	**-2.3**	-0.09	**-2.4**	-0.05	-1.5	-0.08	**-2.2**
stdcf	-0.09	**-2.1**	-0.07	-1.7	-0.09	-1.7	-0.11	**-3.9**	-0.08	**-2.6**	-0.09	**-2.3**	-0.07	**-2.2**	-0.05	-1.4	-0.07	-1.9	-0.08	**-2.1**	-0.05	-1.3	-0.07	-1.7
sue	0.21	**2.7**	0.13	**4.9**	0.27	**7.6**	0.14	1.9	0.11	**4.0**	0.23	**7.5**	0.22	**3.0**	0.13	**5.3**	0.26	**9.2**	0.17	**2.4**	0.10	**4.3**	0.18	**5.8**
tang	0.02	0.4	0.01	0.1	0.09	1.2	0.02	0.4	0.02	0.4	0.11	1.7	0.03	0.5	0.04	0.5	0.13	**2.0**	0.02	0.4	0.02	0.3	0.09	1.3
tb	0.06	1.5	0.06	1.8	0.07	1.6	0.07	1.8	0.06	**2.1**	0.08	**2.8**	0.05	1.2	0.04	1.2	0.08	**2.6**	0.06	1.4	0.03	1.0	0.06	**2.1**
turn	-0.03	-0.2	-0.15	-1.4	-0.31	**-3.8**	-0.16	-1.5	-0.20	**-2.3**	-0.30	**-3.6**	0.01	0.1	-0.08	-0.8	-0.17	-1.8	0.01	0.1	-0.07	-0.7	-0.13	-1.4
zerotrade	-0.03	-0.3	-0.01	-0.7	0.08	1.6	-0.14	-1.8	-0.02	-1.4	-0.06	-0.9	-0.20	**-2.5**	-0.03	-1.8	-0.09	-1.2	-0.20	**-2.5**	-0.04	**-2.0**	-0.11	-1.5

This table presents the results of cross-sectional Fama-MacBeth (1973) regressions of monthly stock returns on each of the 94 firm characteristics one at a time, either after controlling for no other characteristics (column A), or controlling for the characteristics of notable benchmark models (columns B - D). The benchmark models are those of Carhart (1997), Fama and French (2015), and Hou, Xue and Zhang (2015). Three sets of regressions are shown for each benchmark model: Regressions using all stocks and WLS where the weight is the market value of equity for stock i at time t-1 (all stock, value-weighted WLS), regressions using all-but-microcap stocks and OLS (all-but microcap stocks, OLS), and regressions using all stocks and OLS (all stocks, OLS). Microcap stocks are defined as those in month t-1 that have a market value of equity less than the 20th percentile of stocks on the NYSE stock exchange in month t-1. FM coefficients are the means of the monthly estimated coefficients*100; *t*-statistics are taken the time series of monthly coefficient estimates and employ Newey-West adjustments of 12 lags. The sample is all common stocks on the NYSE, AMEX and NASDAQ exchanges with available annual and quarterly Compustat accounting data and CRSP stock return data. Analyst data is from I/B/E/S. Firm-month observations are created using monthly stock returns, including delisting returns, for each month t. Stock returns in month t are matched with the accounting data most recently available as of the end of month t-1, under the assumption that that annual accounting data are available at the end of month t-1 if the firm's fiscal year ended at least six months before the end of month t-1, and that quarterly accounting data are available at the end of month t-1 if the fiscal quarter ended at least four months before the end of month t-1. Intercepts are estimated but not reported.

TABLE 6

Results of Fama-MacBeth (FM) regressions of monthly stock returns on all 94 firm characteristics simultaneously. t-statistics with an absolute value ≥ 3.0 (1.96) are shown boxed and in bold (not boxed and in bold).

	Set of stocks, regression method					
	Column A: All stocks, VWLS		Column B: All-but-microcap stocks, OLS		Column C: All stocks, OLS	
	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	t-stat.
# |*t*-stats| >= 3.0		8		12		27
# |*t*-stats| >= 1.96		28		29		44
agr	-0.02	-0.5	-0.10	$\boxed{\textbf{-3.0}}$	-0.14	$\boxed{\textbf{-4.7}}$
bm	0.21	$\boxed{\textbf{3.6}}$	0.07	**2.1**	0.10	$\boxed{\textbf{3.2}}$
mom12m	0.16	1.7	0.13	1.6	0.10	1.4
mve	-0.25	**-2.5**	-0.17	$\boxed{\textbf{-3.0}}$	-0.67	$\boxed{\textbf{-5.9}}$
operprof	0.01	0.4	0.01	0.5	0.00	0.0
roeq	0.08	**2.1**	0.05	**2.1**	0.09	**2.8**
absacc	-0.01	-0.2	-0.04	-1.5	-0.03	-0.8
acc	-0.15	**-2.9**	-0.06	**-2.2**	-0.04	-1.5
aeavol	0.00	-0.1	-0.01	-0.8	0.01	1.1
age	-0.05	**-2.0**	-0.04	**-2.1**	0.03	1.1
baspread	-0.07	-0.5	0.04	0.5	0.25	**2.8**
beta	0.02	0.2	0.00	0.0	0.07	1.1
bm_ia	-0.24	-1.1	-0.04	-0.5	-0.10	-0.9
cash	0.21	$\boxed{\textbf{3.8}}$	0.17	$\boxed{\textbf{3.4}}$	0.20	$\boxed{\textbf{4.9}}$
cashdebt	0.02	0.4	0.03	1.1	-0.01	-0.5
cashpr	-0.04	**-2.1**	-0.03	-1.7	-0.02	-1.4
cfp	-0.05	-1.1	0.02	0.8	0.08	**2.7**
cfp_ia	0.23	1.1	0.05	0.7	0.12	1.2
chatoia	0.07	**2.6**	0.04	**2.2**	0.06	$\boxed{\textbf{3.1}}$
chcsho	-0.03	**-2.1**	0.00	0.1	-0.05	$\boxed{\textbf{-3.1}}$
chempia	0.09	1.8	0.05	1.4	0.04	1.1
chfeps	0.05	**2.1**	0.07	$\boxed{\textbf{3.2}}$	0.14	$\boxed{\textbf{6.2}}$
chinv	-0.01	-0.2	-0.04	-1.5	-0.06	**-2.3**
chmom	-0.16	$\boxed{\textbf{-3.5}}$	-0.03	-1.1	0.02	0.7
chnanalyst	-0.02	-1.5	-0.07	$\boxed{\textbf{-3.3}}$	-0.08	$\boxed{\textbf{-4.3}}$
chpmia	0.03	0.9	0.02	0.8	0.03	1.2
chtx	0.00	0.1	-0.01	-0.5	0.08	$\boxed{\textbf{5.1}}$
cinvest	-0.04	-1.6	-0.04	**-2.3**	-0.02	-1.1
convind	-0.07	-1.7	-0.04	-0.8	-0.20	$\boxed{\textbf{-3.8}}$
currat	-0.04	-1.4	-0.04	**-2.1**	-0.02	-0.9

	Set of stocks, regression method					
	Column A: All stocks, VWLS		Column B: All-but-microcap stocks, OLS		Column C: All stocks, OLS	
	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	t-stat.
depr	0.01	0.4	0.04	1.3	0.05	1.9
disp	0.00	0.2	-0.02	-1.2	-0.08	**-4.6**
divi	-0.23	-1.9	-0.14	-1.7	-0.23	**-2.9**
divo	0.08	0.7	0.00	0.0	0.03	0.4
dy	-0.05	-1.4	-0.08	**-2.5**	-0.05	**-2.1**
ear	0.08	**3.0**	0.07	**5.7**	0.10	**6.6**
egr	-0.05	-1.5	-0.03	-1.4	-0.01	-0.7
ep	0.15	**2.3**	0.02	0.6	0.14	**3.9**
fgr5yr	0.03	0.4	-0.01	-0.1	0.03	0.8
gma	0.04	1.0	0.09	**2.1**	0.08	1.9
grcapx	-0.06	**-2.9**	-0.05	**-2.9**	-0.06	**-4.0**
grltnoa	-0.06	**-2.0**	-0.04	-1.5	-0.02	-0.7
herf	0.04	1.7	0.01	0.3	-0.05	**-2.5**
hire	-0.04	-0.8	-0.01	-0.3	-0.06	-1.3
idiovol	-0.08	-0.8	-0.04	-0.9	-0.15	**-2.5**
ill	0.18	1.9	-0.07	**-2.1**	0.45	**8.4**
indmom	0.02	0.5	0.11	**2.6**	0.34	**6.5**
invest	0.02	0.4	0.00	-0.1	-0.02	-0.7
ipo	0.05	0.4	-0.04	-0.3	-0.32	**-2.5**
lev	0.02	0.2	0.05	1.1	0.01	0.1
mom1m	-0.51	**-6.9**	-0.37	**-6.5**	-0.81	**-9.4**
mom36m	-0.01	-0.3	-0.02	-1.0	-0.02	-0.8
ms	0.04	1.5	0.06	**2.8**	0.09	**2.7**
mve_ia	-0.01	-0.4	0.00	0.1	0.03	1.3
nanalyst	0.04	1.1	0.04	1.1	0.34	**5.7**
nincr	0.05	**3.3**	0.08	**4.8**	0.12	**6.9**
orgcap	0.00	-0.1	-0.03	-0.8	0.01	0.3
pchcapx_ia	0.03	1.4	0.05	1.9	0.05	1.5
pchcurrat	-0.06	**-2.0**	-0.01	-0.9	0.00	-0.2
pchdepr	0.02	0.7	0.02	1.0	-0.03	-1.3
pchgm_pchsale	0.00	-0.2	0.02	1.4	0.03	1.6
pchsale_pchinvt	-0.01	-0.3	0.03	1.9	0.03	1.9
pchsale_pchrect	-0.01	-0.6	-0.04	**-2.1**	0.02	1.2
pchsale_pchxsga	-0.02	-0.6	-0.02	-1.0	0.00	0.0
pchsaleinv	0.03	1.0	-0.01	-0.5	-0.02	-0.7
pctacc	0.02	0.9	0.02	1.4	0.00	-0.2
pricedelay	0.00	0.0	0.02	1.7	0.00	-0.1

	Set of stocks, regression method					
	Column A: All stocks, VWLS		Column B: All-but-microcap stocks, OLS		Column C: All stocks, OLS	
	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	t-stat.
ps	0.03	1.2	0.03	1.0	0.05	**2.1**
rd	0.04	0.7	0.07	1.4	0.12	**2.2**
rd_mve	0.13	**2.4**	0.14	**3.3**	0.24	**6.5**
rd_sale	-0.02	-0.4	0.01	0.3	0.04	1.6
realestate	0.03	1.3	0.04	**2.0**	0.02	1.2
retvol	-0.51	**-3.8**	-0.26	**-4.9**	-0.44	**-6.3**
roaq	0.00	0.1	0.02	0.5	0.09	**2.0**
roavol	-0.01	-0.3	0.04	1.2	0.01	0.3
roic	0.12	**2.0**	0.03	1.0	0.01	0.2
rsup	0.04	1.0	0.05	**2.2**	0.05	**2.1**
salecash	0.01	0.4	0.01	1.1	-0.03	-1.4
saleinv	-0.03	**-2.1**	0.01	0.4	0.03	**2.4**
salerec	0.02	0.9	0.02	0.8	0.00	0.1
secured	-0.02	-0.7	-0.02	-1.3	-0.03	**-2.0**
securedind	0.13	1.4	0.18	1.4	0.14	1.1
sfe	-0.17	**-2.3**	-0.09	-1.9	0.04	0.9
sgr	-0.11	**-2.5**	0.00	-0.1	-0.04	-1.2
sin	0.30	**2.0**	0.22	1.5	0.50	**3.2**
sp	0.00	0.0	0.03	0.9	0.02	0.4
std_dolvol	-0.06	-0.8	-0.04	-1.5	-0.17	**-4.2**
std_turn	0.12	**2.6**	0.23	**5.0**	0.42	**7.3**
stdcf	-0.04	-1.9	-0.03	-1.4	-0.02	-1.2
sue	0.08	1.7	0.07	**3.2**	0.12	**5.4**
tang	-0.03	-1.0	-0.01	-0.4	0.02	0.5
tb	0.03	1.3	0.03	1.5	0.04	**2.6**
turn	-0.11	**-2.0**	-0.28	**-5.6**	-0.55	**-10.2**
zerotrade	-0.20	**-4.6**	0.00	0.0	-0.34	**-6.9**
Mean # obs.	4,605		1,835		4,605	
Mean adj. R^2	28.6%		15.5%		7.9%	

This table shows the results of monthly Fama-MacBeth (1973) regressions of stock returns in month t when all 94 firm characteristics are simultaneously included as independent variables. Missing observations for a given characteristic in a given month are set to the zero mean of the non-missing values of the characteristic in that month after the non-missing values have been winsorized at the 1st and 99th percentiles and standardized to have a zero mean and unit standard deviation. Three sets of regressions are shown for each benchmark model: Regressions using all stocks and WLS where the weight is the market value of equity for stock i at time t-1 (all stock, VWLS), regressions using all-but-microcap stocks and OLS (all-but microcap stocks, OLS), and regressions using all stocks and OLS (all stocks, OLS). Microcap stocks are defined as those in month t-1 that have a market value of equity less than the 20th percentile of stocks on the NYSE stock exchange in month t-1. FM coefficients are the means of the monthly estimated coefficients*100; *t*-statistics are taken the time series of monthly coefficient estimates and employ Newey-West adjustments of 12 lags. The sample is all common stocks on the NYSE, AMEX and NASDAQ exchanges with available annual and quarterly Compustat accounting data and CRSP stock return data. Analyst data is from I/B/E/S. Intercepts are estimated but not reported.

TABLE 7

Fama-MacBeth (FM) regressions of monthly stock returns on simultaneously including the subset of 28 firm characteristics in Table 6 that are significant per |t-stat.| >= 3.0 in at least one of Columns A, B and C of Table 6. *t*-statistics with an absolute value ≥ 3.0 (1.96) are shown boxed and in bold (not boxed and in bold).

	Column A: All stocks, VWLS		Column B: All-but-microcap stocks, OLS		Column C: All stocks, OLS	
	FM coef.	*t*-stat.	FM coef.	*t*-stat.	FM coef.	*t*-stat.
# |t-stats| >= 3.0		7		9		24
# |*t*-stats| >= 1.96		12		16		27
agr	-0.11	**-3.6**	-0.16	**-5.4**	-0.25	**-7.9**
bm	0.09	1.1	0.02	0.5	0.14	**2.9**
mve	-0.20	**-2.0**	-0.14	**-2.6**	-0.58	**-3.8**
cash	0.22	**3.3**	0.13	1.8	0.19	**2.9**
chatoia	0.04	1.3	0.05	**2.8**	0.06	**3.7**
chcsho	-0.06	**-3.0**	-0.01	-0.8	-0.06	**-3.1**
chfeps	0.06	**2.0**	0.06	**2.5**	0.14	**5.8**
chmom	-0.21	**-3.2**	-0.05	-1.4	0.00	-0.1
chnanalyst	-0.03	-1.5	-0.09	**-2.8**	-0.10	**-3.6**
chtx	0.03	1.0	0.03	1.0	0.09	**5.1**
convind	-0.08	-1.5	0.01	0.2	-0.17	**-2.4**
disp	0.00	0.1	-0.02	-0.8	-0.07	**-3.4**
ear	0.11	**2.8**	0.08	**5.0**	0.12	**6.4**
ep	0.10	1.0	0.05	1.2	0.21	**3.8**
grcapx	-0.08	**-3.1**	-0.06	**-3.6**	-0.09	**-5.4**
ill	0.05	0.5	-0.08	**-2.6**	0.45	**8.3**
indmom	0.05	1.0	0.15	**2.6**	0.38	**6.0**
mom1m	-0.32	**-3.9**	-0.27	**-4.9**	-0.71	**-8.6**
nanalyst	0.04	0.8	0.05	1.1	0.37	**4.5**
nincr	0.07	**3.5**	0.12	**5.0**	0.16	**7.6**
rd_mve	0.02	0.3	0.15	**3.0**	0.25	**5.3**
retvol	-0.44	**-2.6**	-0.24	**-2.6**	-0.45	**-5.6**
sin	0.33	1.9	0.30	1.9	0.53	**3.2**
std_dolvol	-0.07	-0.8	-0.01	-0.4	-0.21	**-3.9**
std_turn	0.09	1.8	0.21	**4.0**	0.45	**7.6**
sue	0.09	1.8	0.08	**4.0**	0.18	**8.4**
turn	-0.05	-0.6	-0.23	**-3.6**	-0.51	**-8.5**
zerotrade	-0.14	**-2.2**	0.00	0.1	-0.26	**-5.3**
Mean # obs.	880		955		2,769	
Mean adj. R^2	33.8%		15.4%		10.1%	

TABLE 7 (continued)

This table shows the results of monthly Fama-MacBeth (1973) regressions of stock returns in month t when the firm characteristics that are simultaneously included as independent variables are limited to the the subset of 28 firm characteristics in Table 6 that are significant per |*t*-stat.| >= 3.0 in at least one of Columns A, B and C of Table 6. Missing observations for a given characteristic in a given month are set to the zero mean of the non-missing values of the characteristic in that month after the non-missing values have been winsorized at the 1st and 99th percentiles and standardized to have a zero mean and unit standard deviation. Three sets of regressions are shown for each benchmark model: Regressions using all stocks and WLS where the weight is the market value of equity for stock i at time t-1 (all stock, VWLS), regressions using all-but-microcap stocks and OLS (all-but microcap stocks, OLS), and regressions using all stocks and OLS (all stocks, OLS). Microcap stocks are defined as those in month t-1 that have a market value of equity less than the 20th percentile of stocks on the NYSE stock exchange in month t-1. FM coefficients are the means of the monthly estimated coefficients*100; *t*-statistics are taken the time series of monthly coefficient estimates and employ Newey-West adjustments of 12 lags. The sample is all common stocks on the NYSE, AMEX and NASDAQ exchanges with available annual and quarterly Compustat accounting data and CRSP stock return data. Analyst data is from I/B/E/S. Intercepts are estimated but not reported

TABLE 8

Statistics on raw and factor-orthogonalized monthly hedge portfolio returns

Panel A: Descriptive statistics for raw monthly hedge portfolio returns

Long top / short bottom decile hedge portfolio	**Mean return**	**Std. dev.**	***t*-stat.**
Portfolio A: VW all stocks hedge portfolio with NYSE decile breakpoints	1.2%	5.3%	3.8
Portfolio B: EW all-but-microcaps hedge portfolio with all-but-microcaps decile breakpoints	1.4%	5.5%	4.5
Portfolio C: EW all stocks hedge portfolio with NYSE decile breakpoints	3.1%	4.7%	11.3

Panel B: Monthly alphas from time-series regressions of the raw monthly hedge portfolio returns on prominent factor returns

		Factor model controls		
Long top / short bottom decile hedge portfolio		**Carhart**	**Fama-French five-factor**	**Hou, Xue and Zhang *q*-factor**
Portfolio A: VW all stocks hedge portfolio with NYSE decile breakpoints	Alpha	1.1%	1.1%	0.9%
	t-stat.	4.9	4.0	3.5
	Adj. R^2	54.5%	30.1%	36.0%
Portfolio B: EW all-but-micro hedge portfolio with all-but-microcaps decile breakpoints	Alpha	1.1%	1.2%	0.8%
	t-stat.	5.4	4.0	3.1
	Adj. R^2	64.9%	27.5%	46.5%
Portfolio C: EW all stocks hedge portfolio with NYSE decile breakpoints	Alpha	3.0%	3.0%	2.8%
	t-stat.	14.3	12.3	12.4
	Adj. R^2	44.0%	31.2%	38.2%

This table presents statistics for monthly hedge portfolio returns calculated as the value-weighted (VW) or equally-weighted (EW) mean return in month t for stocks in the top decile of stocks minus the VW or EW return for stocks in the bottom decile of stocks for the monthly cross-section of predicted returns. Missing observations for a given characteristic in a given month are set to the zero mean of the non-missing values of the characteristic in that month after the non-missing values have been winsorized at the 1st and 99th percentiles and standardized to have a zero mean and unit standard deviation. VW uses the equity market value for month t-1. Decile cutoffs each month are created from NYSE stocks or all-but-micro stocks. Micro stocks are stocks with equity market values less than the 20th percentile of NYSE stocks. Predicted returns are calculated using all characteristics from Table 6 (except for characteristics that require I/B/E/S data) available as of the end of month t-1, and coefficients that are the mean estimated coefficients from rolling 120-month Fama-MacBeth (1973) regressions of month t-119 returns on t-120 characteristics through month t-1 returns on t-2 characteristics. The first estimation window begins January 1st, 1980. The hedge portfolio returns are calculated from Jan. 1990 through Dec. 2014. Panel A presents statistics for the raw hedge portfolio returns. Panel B reports the results from regressing each portfolio's time-series of monthly returns on the factor returns of the Carhart (1997), Fama and French (2015) and Hou, Xue, and Zhang (2015) factor models as provided by the authors of those papers. Alpha is the intercept from the time series regressions and the associated *t*-statistic and regression adjusted R^2 statistics are also reported.

TABLE 9

Statistics on raw and factor-orthogonalized hedge portfolio returns pre-2003 versus post-2003

Panel A: Descriptive statistics for raw monthly hedge portfolio returns pre- and post-2003

	Pre-2003			Post-2003			Post- minus pre-2003	
Portfolio	**Mean return**	**Std. dev.**	***t*-stat.**	**Mean return**	**Std. dev.**	***t*-stat.**	**Diff.**	***t*-stat.**
Portfolio A: VW all stocks hedge portfolio with NYSE decile breakpoints	1.9%	5.5%	4.4	0.5%	4.9%	1.1	-1.4%	-2.3
Portfolio B: EW all-but-microcaps hedge portfolio with all-but-microcaps breakpoints	2.8%	6.0%	5.7	0.1%	4.4%	0.2	-2.7%	-4.4
Portfolio C: EW all stocks hedge portfolio with NYSE decile breakpoints	4.4%	4.4%	12.5	1.7%	4.4%	4.4	-2.8%	-5.2

Panel B: Monthly alphas from time-series regressions of the raw monthly hedge portfolio returns on prominent factor returns pre- and post-2003

Portfolio		**Carhart**	**Fama-French five-factor**	**Hou, Xue and Zhang *q* -factor**
Portfolio A: VW all stocks portfolio with NYSE decile breakpoints	Alpha pre-2003	1.3%	1.5%	1.3%
	t-stat.	4.7	4.3	3.7
	Alpha post-2003	0.7%	0.6%	0.5%
	t-stat.	2.2	1.4	1.3
	Post- minus pre-2003	-0.6%	-1.0%	-0.8%
	t-stat.	-1.5	-1.9	-1.6
	Adj. R^2	54.7%	30.7%	36.3%
Portfolio B: EW all-but-microcaps portfolio with all-but-microcaps decile breakpoints	Alpha pre	1.8%	2.1%	1.6%
	t-stat.	7.1	5.6	4.8
	Alpha post-2003	0.2%	0.0%	-0.1%
	t-stat.	0.6	0.1	-0.3
	Post- minus pre-2003	-1.6%	-2.1%	-1.7%
	t-stat.	-4.4	-3.9	-3.6
	Adj. R^2	66.9%	30.8%	48.6%

TABLE 9 (continued)

Portfolio		Carhart	Fama-French five-factor	Hou, Xue and Zhang *q* -factor
Portfolio C: EW all stocks portfolio with NYSE decile breakpoints	Alpha pre-2003	3.9%	4.0%	3.8%
	t-stat.	14.6	13.1	13.0
	Alpha post-2003	1.9%	1.7%	1.7%
	t-stat.	6.4	5.3	5.5
	Post- minus pre-2003	-2.0%	-2.3%	-2.1%
	t-stat.	-5.1	-5.2	-5.0
	Adj. R^2	48.3%	36.8%	42.8%

This table presents statistics for monthly hedge portfolio returns pre- versus post-2003, where hedge portfolio returns are calculated as the value-weighted (VW) or equally-weighted (EW) mean return in month t for stocks in the top decile of stocks minus the VW or EW return for stocks in the bottom decile of stocks for the monthly cross-section of predicted returns. Missing observations for a given characteristic in a given month are set to the zero mean of the non-missing values of the characteristic in that month after the non-missing values have been winsorized at the 1st and 99th percentiles and standardized to have a zero mean and unit standard deviation. VW uses the equity market value for month t-1. Decile cutoffs each month are created from NYSE stocks or all-but-micro stocks. Micro stocks are stocks with equity market values less than the 20th percentile of NYSE stocks. Predicted returns are calculated using all characteristics from Table 6 (except for characteristics that require I/B/E/S data) available as of the end of month t-1, and coefficients that are the mean estimated coefficients from rolling 120-month Fama-MacBeth (1973) regressions of month t-119 returns on t-120 characteristics through month t-1 returns on t-2 characteristics. The first estimation window begins January 1st, 1980. The hedge portfolio returns are calculated from Jan. 1990 through Dec. 2014. Panel A presents statistics for the raw hedge portfolio returns. Panel B reports the results from regressing each portfolio's time-series of monthly returns on the factor returns of the Carhart (1997), Fama and French (2015) and Hou, Xue, and Zhang (2015) factor models as provided by the authors of those papers. Alpha is the intercept from the time series regressions and the associated *t*-statistic and regression adjusted R^2 statistics are also reported.

TABLE 10

Fama-MacBeth (1973) cross-sectional regressions of monthly stock returns on all firm characteristics pre- versus post-2003

	Table 6 Fama-MacBeth regressions, pre-2003						**Table 6 Fama-MacBeth regressions, post-2003**					
	Set of stocks, regression method						**Set of stocks, regression method**					
	Column A_pre: All stocks, VWLS		**Column B_pre: All-but-microcaps, OLS**		**Column C_pre: All stocks, OLS**		**Column A_post: All stocks, VWLS**		**Column B_post: All-but-microcaps, OLS**		**Column C_post: All stocks, OLS**	
	FM coef.	***t*-stat.**	**FM coef.**	***t*-stat.**	**FM coef.**	***t*-stat.**	**FM coef.**	***t*-stat.**	**FM coef.**	***t*-stat.**	**FM coef.**	***t*-stat.**
# |t-stats| >= 3.0		11		16		25		2		1		13
# |t-stats| >= 1.96		26		29		40		9		10		33
agr	-0.03	-0.4	-0.09	**-2.4**	-0.16	**-4.3**	-0.02	-0.3	-0.10	-1.9	-0.10	**-2.1**
bm	0.31	**4.2**	0.11	**2.8**	0.14	**3.5**	0.03	0.3	-0.02	-0.6	0.03	0.6
mom12m	0.31	**3.3**	0.28	**3.8**	0.23	**4.6**	-0.12	-0.7	-0.15	-0.9	-0.13	-0.8
mve	-0.27	**-2.1**	-0.24	**-3.4**	-0.75	**-5.7**	-0.21	-1.3	-0.04	-0.5	-0.52	**-2.6**
operprof	0.02	0.4	0.00	-0.1	0.00	0.1	0.00	0.0	0.03	1.6	0.00	-0.1
roeq	0.13	**2.4**	0.10	**3.0**	0.12	**2.7**	-0.01	-0.2	-0.03	-1.0	0.03	0.9
absacc	-0.04	-0.6	-0.04	-1.1	-0.04	-1.3	0.05	0.7	-0.05	-1.0	0.00	0.0
acc	-0.20	**-3.0**	-0.10	**-3.0**	-0.06	-1.8	-0.05	-0.7	0.01	0.3	-0.02	-0.3
aeavol	0.02	0.6	0.00	-0.1	0.01	0.9	-0.04	-0.9	-0.03	-1.4	0.01	0.6
age	-0.07	-1.7	-0.04	-1.6	0.05	1.3	-0.03	-1.1	-0.04	-1.6	0.00	-0.2
baspread	0.02	0.2	0.04	0.6	0.41	**4.3**	-0.26	-1.0	0.02	0.2	-0.05	-0.3
beta	0.06	0.4	0.02	0.2	0.06	0.8	-0.05	-0.4	-0.03	-0.3	0.09	0.9
bm_ia	-0.35	-1.0	-0.06	-0.4	-0.15	-0.9	-0.02	-0.4	-0.02	-0.3	-0.02	-0.3
cash	0.28	**4.1**	0.26	**4.0**	0.20	**3.8**	0.08	0.9	0.02	0.3	0.20	**3.2**
cashdebt	-0.04	-0.6	0.05	1.0	-0.02	-0.6	0.13	1.6	0.01	0.3	0.00	-0.1
cashpr	-0.03	-1.1	-0.02	-0.8	-0.04	-1.8	-0.07	**-2.4**	-0.05	-1.7	0.01	0.4
cfp	-0.04	-0.7	0.02	0.5	0.07	1.6	-0.08	-0.8	0.03	0.8	0.12	**2.5**

cfp_ia	0.37	1.1	0.04	0.4	0.17	1.1	-0.03	-0.5	0.07	1.3	0.03	0.5
chatoia	0.09	**3.0**	0.06	**2.5**	0.04	1.5	0.03	0.6	0.02	0.5	0.09	**4.0**
chcsho	-0.02	-1.3	0.01	0.2	-0.06	**-2.7**	-0.04	-1.9	-0.01	-0.4	-0.04	-1.6
chempia	0.04	0.6	-0.01	-0.3	0.00	0.0	0.17	**2.9**	0.16	**3.7**	0.11	**2.2**
chfeps	0.08	**2.2**	0.11	**3.7**	0.19	**7.3**	0.02	0.8	0.03	1.2	0.09	**3.0**
chinv	0.03	0.6	-0.02	-0.6	-0.06	-1.7	-0.09	-1.8	-0.07	**-2.0**	-0.06	-1.7
chmom	-0.19	**-3.2**	-0.03	-0.8	0.06	1.4	-0.11	-1.6	-0.03	-0.7	-0.04	-0.8
chnanalyst	-0.02	-1.1	-0.09	**-2.5**	-0.09	**-2.8**	-0.02	-1.0	-0.05	**-2.8**	-0.08	**-3.1**
chpmia	0.01	0.2	0.03	1.2	0.03	0.9	0.06	1.5	0.00	-0.1	0.04	0.9
chtx	-0.04	-1.0	-0.01	-0.4	0.08	**4.2**	0.08	**2.8**	-0.01	-0.4	0.06	**3.0**
cinvest	-0.06	**-2.1**	-0.05	**-3.1**	-0.01	-0.7	0.00	0.0	-0.02	-0.5	-0.03	-0.8
convind	-0.10	**-2.1**	-0.07	-1.5	-0.26	**-4.2**	-0.01	-0.2	0.04	0.4	-0.08	-0.9
currat	-0.04	-1.0	-0.04	-1.6	0.00	0.1	-0.05	-1.3	-0.04	-1.4	-0.06	**-2.0**
depr	0.03	0.7	0.05	1.4	0.07	**2.0**	-0.02	-0.5	0.01	0.2	0.01	0.3
disp	0.02	0.4	-0.03	-1.0	-0.10	**-4.6**	-0.01	-0.3	-0.02	-0.6	-0.05	**-2.4**
divi	-0.40	**-2.6**	-0.20	-1.8	-0.30	**-3.0**	0.08	0.4	-0.03	-0.3	-0.11	-0.9
divo	0.10	0.6	0.06	0.4	0.14	1.4	0.05	0.4	-0.12	-0.8	-0.18	-1.6
dy	-0.05	-1.0	-0.10	**-2.3**	-0.05	-1.6	-0.06	-1.1	-0.03	-1.2	-0.06	-1.4
ear	0.09	**2.5**	0.07	**5.2**	0.09	**5.4**	0.06	1.8	0.07	**2.7**	0.11	**4.2**
egr	-0.08	-1.7	-0.06	**-2.1**	-0.04	-1.5	0.00	0.1	0.03	0.9	0.04	1.3
ep	0.19	**2.3**	0.05	1.3	0.16	**3.8**	0.08	0.7	-0.04	-0.5	0.12	1.6
fgr5yr	0.05	0.4	0.01	0.1	0.08	1.4	0.00	0.1	-0.03	-0.7	-0.03	-1.1
gma	0.08	1.4	0.10	1.7	0.10	1.8	-0.02	-0.3	0.07	1.3	0.04	0.9
grcapx	-0.08	**-3.1**	-0.04	**-2.1**	-0.05	**-2.4**	-0.03	-0.8	-0.05	**-2.0**	-0.08	**-3.9**
grltnoa	-0.06	-1.7	-0.05	**-2.1**	-0.04	-1.3	-0.05	-1.0	-0.01	-0.2	0.02	0.6
herf	0.08	**2.2**	0.02	0.6	-0.05	-1.8	-0.02	-0.8	-0.02	-0.9	-0.04	**-2.1**
hire	-0.04	-0.6	0.03	0.6	-0.02	-0.4	-0.05	-0.7	-0.08	-1.7	-0.12	**-2.1**
idiovol	-0.22	-1.7	-0.12	-2.0	-0.23	**-2.8**	0.19	1.6	0.10	1.5	0.00	0.0
ill	0.36	**3.1**	-0.03	-1.2	0.56	**8.4**	-0.16	-1.6	-0.14	-1.8	0.25	**4.8**

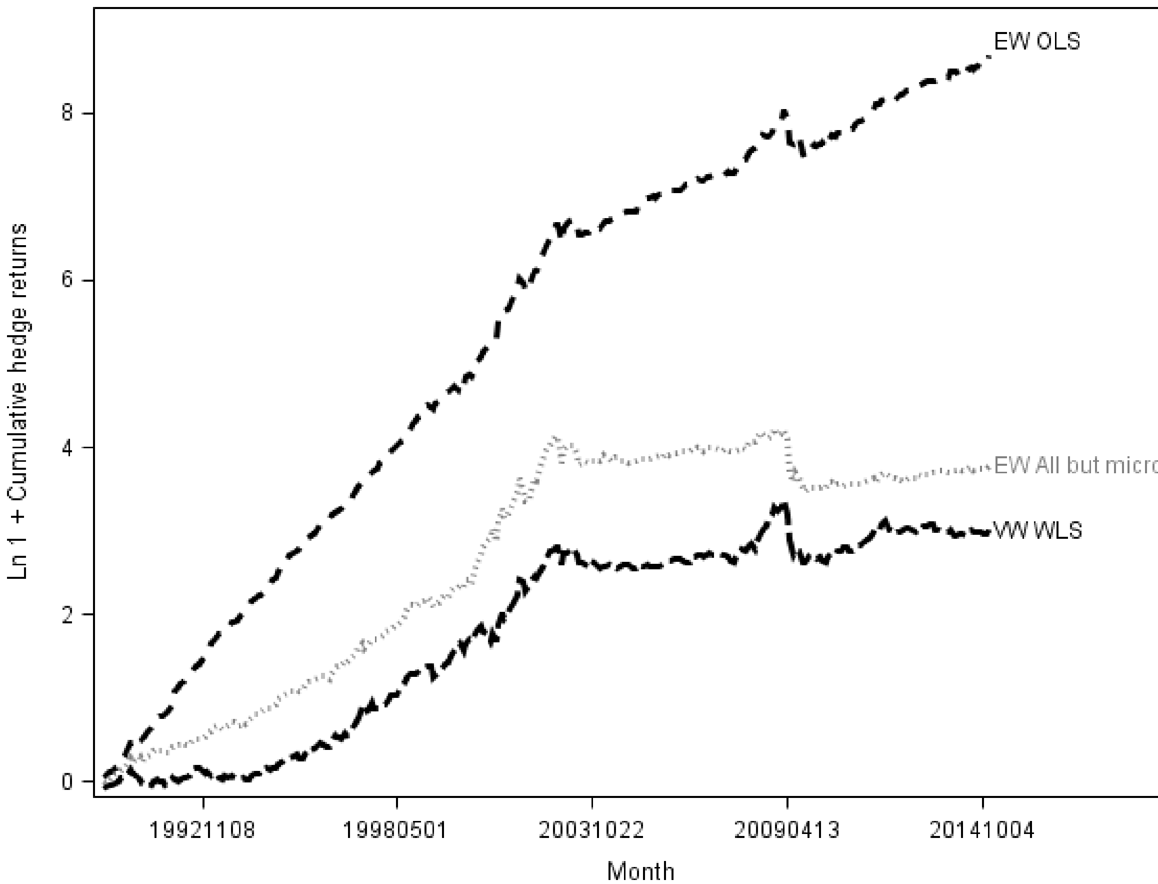
indmom	0.01	0.2	0.11	1.8	0.41	**5.6**	0.03	0.6	0.10	**2.4**	0.22	**4.9**
invest	-0.03	-0.5	-0.04	-1.1	-0.09	**-2.3**	0.10	**2.2**	0.07	1.7	0.10	**2.1**
ipo	-0.05	-0.3	-0.17	-1.0	-0.36	**-2.9**	0.23	1.1	0.20	0.8	-0.25	-0.8
lev	0.13	**2.0**	0.13	**2.1**	0.11	**2.0**	-0.20	**-2.0**	-0.08	-1.2	-0.18	-1.4
mom1m	-0.65	**-8.4**	-0.49	**-7.6**	-1.07	**-14.9**	-0.23	**-2.1**	-0.16	-1.9	-0.31	**-3.0**
mom36m	-0.07	-1.5	-0.05	-1.7	-0.05	-1.2	0.11	**2.6**	0.02	0.7	0.02	0.4
ms	0.09	**2.3**	0.09	**3.1**	0.16	**4.4**	-0.04	-1.1	0.00	0.2	-0.06	-1.8
mve_ia	0.00	0.0	0.02	0.6	0.04	1.4	-0.02	-0.7	-0.02	-0.6	0.01	0.3
nanalyst	0.01	0.2	0.13	**2.8**	0.50	**7.5**	0.07	1.4	-0.05	-1.1	0.18	**2.5**
nincr	0.04	1.9	0.09	**4.3**	0.14	**6.4**	0.08	**3.6**	0.06	**2.3**	0.09	**3.1**
orgcap	0.00	-0.1	-0.01	-0.3	0.02	0.7	-0.01	-0.1	-0.05	-1.3	-0.02	-0.5
pchcapx_ia	0.05	1.6	0.02	0.9	0.00	0.0	0.01	0.2	0.10	1.8	0.14	1.7
pchcurrat	-0.07	-1.9	-0.02	-1.0	-0.01	-0.3	-0.04	-0.9	-0.01	-0.2	0.00	0.1
pchdepr	0.02	0.7	0.00	-0.2	-0.05	-1.8	0.01	0.1	0.06	1.9	0.02	0.6
pchgm_pchsale	-0.02	-0.7	0.02	0.7	0.02	0.9	0.03	1.0	0.04	1.4	0.04	1.7
pchsale_pchinvt	0.00	0.1	0.03	1.3	0.02	0.9	-0.02	-0.6	0.03	1.7	0.06	**2.4**
pchsale_pchrect	-0.01	-0.2	-0.05	-1.8	0.01	0.5	-0.03	-0.9	-0.03	-1.0	0.04	1.9
pchsale_pchxsga	-0.05	-1.1	-0.03	-1.2	-0.01	-0.2	0.04	1.0	0.00	0.1	0.01	0.3
pchsaleinv	0.05	1.3	0.01	0.6	0.02	0.8	-0.02	-0.7	-0.06	-1.8	-0.09	**-2.3**
pctacc	0.00	0.0	0.03	1.5	-0.01	-0.3	0.06	1.7	0.01	0.3	0.00	0.1
pricedelay	0.03	0.6	0.00	0.2	-0.01	-0.4	-0.05	-0.9	0.06	**2.2**	0.01	0.7
ps	0.04	1.0	0.05	1.6	0.07	**2.0**	0.02	0.6	-0.02	-0.5	0.02	0.6
rd	0.00	0.0	0.08	1.3	0.16	**2.2**	0.12	1.1	0.06	0.6	0.04	0.5
rd_mve	0.10	1.8	0.17	**2.9**	0.25	**5.4**	0.18	1.6	0.08	**2.0**	0.23	**3.6**
rd_sale	0.01	0.1	0.02	0.5	0.06	1.9	-0.06	-1.0	0.00	0.0	0.01	0.1
realestate	0.03	1.1	0.04	1.5	0.02	0.5	0.02	0.7	0.04	1.5	0.04	1.7
retvol	-0.78	**-5.5**	-0.39	**-7.5**	-0.49	**-5.9**	0.00	0.0	0.00	0.0	-0.36	**-2.9**
roaq	-0.01	-0.2	0.01	0.1	0.08	1.5	0.04	0.4	0.04	0.8	0.09	1.5
roavol	0.00	0.0	0.05	1.2	0.03	0.8	-0.03	-0.4	0.01	0.3	-0.03	-0.8

roic	0.19	**2.9**	0.06	1.5	0.06	1.6	-0.02	-0.2	-0.02	-0.4	-0.10	**-2.2**
rsup	0.02	0.3	0.05	2.0	0.06	1.9	0.08	1.4	0.04	1.1	0.04	1.1
salecash	0.00	0.2	0.01	0.5	-0.02	-0.8	0.01	0.4	0.03	1.0	-0.04	-1.3
saleinv	-0.03	-1.5	0.00	-0.3	0.03	**2.2**	-0.04	-1.6	0.02	1.0	0.04	1.3
salerec	0.03	0.8	0.02	0.6	0.01	0.3	0.02	0.4	0.02	0.5	-0.01	-0.3
secured	-0.01	-0.2	-0.01	-0.6	-0.03	-1.2	-0.04	-0.9	-0.04	-1.4	-0.05	-1.9
securedind	0.18	1.2	0.27	1.4	0.17	0.8	0.05	1.4	0.01	0.2	0.08	1.5
sfe	-0.26	**-2.5**	-0.18	**-3.8**	-0.08	**-2.2**	-0.08	-0.8	0.01	0.1	0.16	**2.4**
sgr	-0.11	-1.9	0.00	0.0	-0.01	-0.4	-0.11	-1.7	-0.01	-0.2	-0.08	-1.6
sin	0.19	0.9	0.16	0.9	0.54	**2.6**	0.49	**3.3**	0.31	1.2	0.45	1.8
sp	-0.07	-0.8	0.03	0.6	-0.06	-1.1	0.14	1.9	0.05	1.0	0.18	**2.3**
std_dolvol	-0.13	-1.6	-0.07	**-2.3**	-0.17	**-3.5**	0.07	0.5	0.02	0.7	-0.17	**-2.2**
std_turn	0.21	**4.0**	0.37	**10.1**	0.58	**13.8**	-0.05	-0.7	-0.04	-0.8	0.12	1.2
stdcf	-0.03	-1.2	-0.01	-0.6	-0.02	-1.0	-0.07	-1.5	-0.06	-1.5	-0.03	-0.7
sue	0.04	1.1	0.05	**2.2**	0.10	**3.5**	0.16	1.4	0.10	**2.5**	0.16	**5.2**
tang	-0.06	-1.5	-0.03	-0.9	0.05	1.3	0.02	0.5	0.02	0.5	-0.05	-0.8
tb	0.02	0.7	0.03	1.0	0.03	1.7	0.05	1.5	0.04	1.2	0.06	**2.1**
turn	-0.17	**-2.5**	-0.40	**-7.8**	-0.66	**-12.3**	0.01	0.1	-0.06	-1.0	-0.32	**-4.0**
zerotrade	-0.24	**-4.4**	-0.07	**-3.7**	-0.45	**-8.3**	-0.12	-1.9	0.14	1.8	-0.12	**-2.2**
Mean # obs.		4,909		1,896		4,909		4,027		1,720		4,027
Mean adj. R^2		28.0%		15.4%		7.7%		29.8%		15.7%		8.3%

This table presents the results of estimating the regressions reported in Table 6 separately pre-2003 versus post-2003, where post-2003 is defined as beginning Jan. 2003. All 94 firm characteristics are simultaneously included as independent variables. Missing observations for a given characteristic in a given month are set to the zero mean of the non-missing values of the characteristic in that month after the non-missing values have been winsorized at the 1st and 99th percentiles and standardized to have a zero mean and unit standard deviation. Three sets of regressions are shown for each benchmark model: Regressions using all stocks and WLS where the weight is the market value of equity for stock i at time t-1 (all stock, VWLS), regressions using all-but-microcap stocks and OLS (all-but microcap stocks, OLS), and regressions using all stocks and OLS (all stocks, OLS). Microcap stocks are defined as those in month t-1 that have a market value of equity less than the 20th percentile of stocks on the NYSE stock exchange in month t-1. FM coefficients are the means of the monthly estimated coefficients*100; t-statistics are taken the time series of monthly coefficient estimates and employ Newey-West adjustments of 12 lags. The sample is all common stocks on the NYSE, AMEX and NASDAQ exchanges with available annual and quarterly Compustat accounting data and CRSP stock return data. Analyst data is from I/B/E/S. Intercepts are estimated but not reported.

FIGURE 1

Plot of ln(1 + cumulative mean monthly raw hedge portfolio returns to predicting the cross-section of returns using all 94 characteristics except those based on I/B/E/S data), separately for [1] value-weighted returns for all stocks with NYSE decile breakpoints (VW WLS), [2] equally-weighted returns for all-but-microcap stocks with all-but-microcap decile breakpoints (EW all-but-micro), and [3] equally-weighted returns for all stocks with NYSE decile breakpoints (EW OLS).



This figure plots the natural log of 1 + the cumulative mean monthly raw hedge portfolio returns to predicting the cross-section of returns using all 94 characteristics, less the 8 characteristics that are based on I/B/E/S data). Mean monthly raw hedge portfolio returns calculated as the value-weighted (VW) or equally-weighted (EW) mean return in month t for stocks in the top decile of stocks minus the VW or EW return for stocks in the bottom decile of stocks for the monthly cross-section of predicted returns. Missing observations for a given characteristic in a given month are set to the zero mean of the non-missing values of the characteristic in that month after the non-missing values have been winsorized at the 1st and 99th percentiles and standardized to have a zero mean and unit standard deviation. VW uses the equity market value for month t-1. Decile cutoffs each month are created from NYSE stocks or all-but-micro stocks. Micro stocks are stocks with equity market values less than the 20th percentile of NYSE stocks. Predicted returns are calculated using all characteristics from Table 6 (except for characteristics that require I/B/E/S data) available as of the end of month t-1, and coefficients that are the mean estimated coefficients from rolling 120-month Fama-MacBeth (1973) regressions of month t-119 returns on t-120 characteristics through month t-1 returns on t-2 characteristics. The first estimation window begins January 1st, 1980. The hedge portfolio returns are calculated from Jan. 1990 through Dec. 2014.