# Long Run Stock Returns after Corporate Events Revisited

Hendrik Bessembinder

W.P. Carey School of Business

Arizona State University

Feng Zhang

David Eccles School of Business

University of Utah

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Abstract

Kolari, Pynnonen, and Tuncez rely on simulation outcomes to criticize the normalization of firm characteristics employed by Bessembinder and Zhang (2013) to assess returns after major corporate events. However, their simulation outcomes simply verify that a non-linear normalization is inappropriate if the true relation is linear. The relation between log returns and firm characteristics is unknown, but is unlikely to be linear, as the distribution of firm characteristics is strongly skewed. Here, we report on bootstrap simulations that show our methods provide unbiased estimates with appropriate statistical size and high power to detect abnormal returns when implemented in actual data. Kolari, Pynnonen, and Tuncez also provide empirical estimates that comprise useful sensitivity tests. Their results verify that firm characteristics are useful in assessing whether returns to event firms are abnormal, largely confirm our conclusions with regard to SEOs, M&As, and dividend increases, but show that conclusions regarding IPOs depend on implementation choices.

# I. Introduction

In our 2013 Journal of Financial Economics paper (BZ hereafter) we study returns in the months after four important corporate events, initial public offerings of stock (IPOs), secondary offerings of stock (SEOs), dividend initiations, and merger and acquisition (M&A) events. We show that firms engaging in these events differ systematically from size and book-to-market matched firms in terms of additional firm characteristics that are known to be related to returns, including return momentum, illiquidity, and rate of capital investment. We propose (BZ expression 3) to control for differences in firm characteristics by testing whether intercepts in regressions of the difference in log returns across event and control firms on differences in firm characteristics differ from zero. In implementing BZ expression (3) we employed a normalization of firm characteristics that replaces raw characteristics with percentile ranks.

Kolari, Pynnonen, and Tuncez (2017, KPT hereafter) concur that this approach generally has merit, but criticize the specific normalization of explanatory variables we employed, asserting that it induces “incremental nonlinearity”, “randomizes regression relations” and more broadly leads to “severe biases”. To support their assertions, KPT rely on simulations where the true regression relation is specified to be linear, and explanatory variables are drawn from symmetric distributions. The simulation outcomes indicate that the normalization biases, and increases the standard error of, the estimated regression intercept under the specified assumptions.

However, in our view the simulation outcomes reported by KPT are simply not informative regarding the econometric merits of the methods we implemented in BZ. It is self-evident that a non-linear normalization of explanatory variables will introduce econometric problems if the true relation between the dependent and explanatory variables is linear. However, we know of no reason (and KPT provide none) rooted in either theory or empirical practice to believe that the actual relation between log firm returns and firm characteristics should be linear. While asset pricing models typically imply that firm returns should be linear in factor loadings (i.e., betas), theory does not typically make similar predictions regarding firm characteristics. Many firm characteristics, including for example market capitalization, illiquidity measures, trading activity, market to book ratios, and rates of capital investment are not distributed symmetrically, but are strongly skewed in the cross section. It therefore seems highly improbable that the true relation between firm returns and characteristics is linear. Indeed, finance researchers routinely rely on non-linear transformations of firm characteristics when seeking to explain firm returns.

Greene (2000, Chapter 8), notes that when functional forms are non-linear researchers can employ transformations of explanatory variables such as "logarithms, exponentials, reciprocals, transcendental functions, polynomials, products, ratios, and so on." The transformation from raw data to percentiles used in BZ is simply a rank transformation. Rank transformation has a long history in econometrics, dating at least to Spearman's (1904) development of the rank correlation coefficient. Conover and Iman (1981) observe that rank transformations are particularly useful when the variables of interest are not symmetrically distributed.

We report herein on simulation results that *are* relevant to assessing the econometric merits of the normalization we employed in BZ. In particular, we follow Brown and Warner (1980, 1985), Barber and Lyon (1997), Kothari and Warner (1997), Lyon, Barber, and Tsai (1999), and Loughran and Ritter (2000) in conducting bootstrap simulations that involve actual stock returns. In particular, we randomly select "event" firms and size-matched "control" firms, relying on the actual distribution of firm characteristics and the actual but unknown relation between returns and characteristics.

The bootstrap simulation results confirm that the methods we used in BZ have desirable econometric properties when implemented in actual data. Since firms are selected at random, no abnormal performance should be detected. Indeed, the mean intercepts estimated across 1,000 bootstrap simulations when implementing the BZ specification for random firms are economically infinitesimal (0.1 basis point per month without quadratic terms, and 0.5 basis point per month with quadratic terms), which verifies that the method we used in BZ produces unbiased intercept estimates in actual data under the null hypothesis. Further, the methods used in BZ display appropriate size under the null hypothesis and high statistical power when we add artificial abnormal returns to randomly selected event firms. In short, while the KPT simulations show that the normalization of explanatory variables we used in BZ would be flawed if the true relation were linear and explanatory variables were distributed symmetrically, bootstrap simulations in real world data support that the methods we used in BZ are econometrically sound in the setting where we implement them.

In addition to simulation outcomes, KPT report empirical results that rely on BZ expression (3), but assume a linear relation between log returns and explanatory variables. We note that, with the exception of IPOs, KPT report (Tables 4 and 5) estimated intercepts estimated from pooled data that are economically small (20 basis points per month for M&As, 24 basis points per month for SEOs, and 15 basis points per month for dividend initiations). When we implement the Fama-MacBeth (FM) procedure (we reported FM results in BZ, but KPT do not) and include quadratic terms, we find insignificant intercepts for *all four* events, including IPOs, even when using the non-normalized characteristics as KPT recommend.

KPT note that our requirement in BZ that twelve months of return data be available in order to estimate beta coefficients precludes the examination of IPO returns in the months immediately following the IPO. They observe that most of these months can be recovered by estimating betas using daily returns for just a single month. Like them, we find negative and significant intercept estimates for IPOs when relying on the linear specification that KPT recommend in an IPO sample that is expanded by estimating betas in this manner. However, we estimate an economically small (negative one basis point per month) intercept for IPOs even in the expanded sample when we rely on our original non-linear transformation of the explanatory variables.

While the simulation evidence provided by KPT is uninformative and their specific econometric concerns are unfounded, their empirical results comprise useful sensitivity tests regarding the robustness of the findings we report in BZ. In particular, when implementing BZ expression (3) to control for differences in firm characteristics across event and control firms, they show that a linear specification with a simple scaling of coefficient estimates leads, in pooled estimation, to estimated abnormal performance that is economically small, with the exception of IPOs. While KPT's results broadly confirm that firm characteristics are relevant in assessing whether post-event returns are abnormal, with regard to IPOs their sensitivity tests show that conclusions are affected by implementation issues, including whether explanatory variables are transformed and also depending on whether empirical results are pooled or are obtained by the Fama-MacBeth method.

## II. Relevant Simulation Evidence

As noted in the introduction, we view the simulation evidence provided by KPT to be uninformative, because the simulations are conducted under the assumptions (i) that the true relation between the dependent and explanatory variables is linear, and (ii) that explanatory variables are distributed symmetrically. We know of no reason to think that these assumptions are relevant when assessing relations between log firm returns and firm characteristics, nor do KPT provide any. In fact, simulation evidence under these assumptions seems to us to be overkill --- it is obvious that a non-linear transformation of explanatory variables will induce econometric estimation problems given these assumptions.

In Table 1 we report the skewness, estimated from the pooled distribution, of the firm characteristics we employed in BZ. Results are reported for each of the four corporate events, for the characteristics of event firms and the difference in characteristics between event and control firms. In contrast to the assumptions underlying the KPT simulations, these characteristics are not symmetric, but are skewed, in some cases severely. While the skewness of estimated market beta coefficients is moderate, the standardized skewness coefficients in most cases exceed ten, and in the case of capital investment exceed one hundred in some samples. This strong skewness in firm characteristics is at odds with KPT's assumption that explanatory variables are symmetric, and also casts substantial doubt on their assumption that the true relation between log returns and explanatory variables is linear. While theory provides no firm guidance as to the correct functional form for relations between firm returns (simple or log) and firm characteristics, the strong skewness in explanatory variables leads many researchers (see, for example Fama and French, 1992 and Haugen and Baker, 1996, among many possible examples) to use non-linear transformations of the variables to explain firm returns.

In this section we provide simulation evidence that is directly relevant to assessing the econometric properties of the methods we used in BZ. In particular, we follow Brown and Warner (1980, 1985), Barber and Lyon (1997), Kothari and Warner (1997), Lyon, Barber, and Tsai (1999), and Loughran and Ritter (2000), which comprise the most prominent simulation analyses in the event study literature, in conducting bootstrap simulations to assess the properties of estimates obtained using our econometric methods when implemented in actual return and characteristic data.

In each month from 1980 to 2010 (the BZ sample period), we divide all commons tocks in the CRSP universe with requisite firm characteristic data into twenty five groups based on their market capitalization as of the latest June.   We randomly choose one "event" firm from each size group in each month, and we assign a random size-matched "control" firm from the same size portfolio. Having identified these "pseudo event" firms and their controls, we implement the test delineated in BZ expression (3), using data for the sixty months subsequent to the random event month. Specifically, we regress the difference in log return between the pseudo event firm and its matching firm on the normalized differences in firm characteristics in pooled OLS regressions, and test whether the intercept estimate is zero.[1]  We repeat the bootstrap procedure 1,000 times.

Panel A of Table 2 reports on the resulting intercept estimates, when BZ expression (3) is estimated using the normalization of characteristics we employed in BZ, with and without quadratic terms.   Since firms are assigned randomly, no abnormal performance should be detected if the model is properly specified.   The specification we used in BZ performs well.   Across the 1,000 simulated tests, the mean intercept is just -0.1 basis points per month without quadratic terms and -0.5 basis points per month with quadratic terms.   The median intercept is -0.2 basis points per month without quadratic terms and -0.4 basis points per month with quadratic terms.   That is, intercepts estimated by our methods in actual data average almost exactly zero when there is no abnormal performance to detect.  These results therefore support the conclusion that the methods we employed in BZ provide unbiased intercept estimates in actual data, in sharp contrast to the assertions made by KPT.

In Panel B of Table 2 we report evidence regarding the probability that the methods in BZ falsely reject the null hypothesis of no performance, i.e. the size of the statistics.  The table reports the

[1] Simulations results are similar when we implement the Fama-MacBeth method rather than pooled estimation.

percentage of the 1,000 simulations where the t-statistic for the estimated intercept indicates rejection of the null hypothesis at the indicated significance level. For example, when the theoretical significance level is 5% (so a properly specified test should reject 2.5% of the time in each tail), the BZ method without quadratic terms rejects 2.9% of the time in the left tail and 2.8% of the time in the right tail. The BZ method with quadratic terms rejects 2.4% of the time in the left tail and 1.7% of the time in the right tail. Overall, the results reported in Table 2 indicate that the methods we employed in BZ perform well in actual data in terms of rejecting the null hypothesis with approximately the correct frequency.

Finally, we assess the power of the BZ method by artificially adding abnormal performance to randomly selected "event" firms. Following Barber and Lyon (1997) (see their Table 6) we inject abnormal performance ranging from 15% per year (about 1.25% per month) to -15% per year. Panel C of Table 2 reports the percentage of the 1,000 simulations resulting in rejection of the null hypothesis at the five percent significance level. The results show that the BZ method rejects the null hypothesis in all of the 1,000 simulations, with or without the use of quadratic terms, for abnormal performance of -15%, -10%, 10%, and 15% per year.

The BZ method without quadratic terms also rejects in 100% of the simulations when abnormal performance is -5% or 5% per year, while the BZ method with quadratic terms rejects in 96.2% and 95.0% of the simulations for these levels of performance. By comparison, the nine return benchmark methods evaluated by Barber and Lyons (1997, Table 6) achieved rejection rates, also based on 5% and -5% per year of injected abnormal performance and 1,000 simulations, ranging from 9% to 39%. On balance, these results show that the methods used in BZ have high statistical power when implemented in actual data.

In contrast to the simulation results reported by KPT, which simply verify the intuition that non-linear transformations of explanatory variables introduce econometric problems when the true relation is linear, we report bootstrap simulation results that are relevant to assessing the performance of the methods used in BZ, because they are implemented in actual data and therefore incorporate the actual distribution of firm characteristics and the unknown actual relation between firm returns and characteristics. In sharp contrast to KPT's claims that our methods introduce "severe biases" and other problems, the results of these bootstrap simulations show that methods used in BZ deliver unbiased intercept estimates with appropriate rejection rates and high statistical power when implemented in actual data.

## III. Robustness and interpretation of results reported by KPT

In addition to their simulation results, KPT present empirical results that we view as comprising useful robustness exercises. In particular, KPT propose to estimate BZ expression (3) based on a linear or quadratic relation between log returns and characteristics. They then scale each estimated slope coefficient by the standard deviation of the corresponding characteristic. Based on their resulting estimates, they conclude that "even though the event firms and their controls differ in terms of various characteristics, these differences do not generally eliminate abnormal returns as measured by alphas (intercepts)."

We note, however, that the results reported by KPT support that the apparently abnormal returns are indeed fully eliminated in the case of dividend initiations, and are economically small in the cases of M&As and SEOs, even with simple linear specifications. Further, the apparently abnormal returns after IPOs are explained by specifications that rely on their recommended standardization, but that they do not report.

In particular, we focus attention on the intercept estimates in the columns labeled "Linear" in KPT Tables 4 and 5. These intercepts are estimates of the average abnormal monthly log return to event firms, after controlling in a linear regression for differences in characteristics. For M&As and SEOs (Table 4) the point estimates are -0.198% and -0.237% per month, respectively. Despite t-statistics of -2.00 and -2.31, respectively, these estimates are economically modest. For dividend initiations the point estimate is -0.148% per month (Table 5), which is both economically small and statistically insignificant (t-statistic = -1.13). We conclude that the KPT robustness tests show that, even with linear estimation and their recommended standardization, differences in firm characteristics do have substantial explanatory power for the apparently abnormal returns to firms engaging in M&As, SEOs, and dividend initiations. Only in the case of IPOs do KPT report an economically substantive intercept (-0.531% per month, Table 5) from the linear specification that uses their recommended standardization.

We note, however, that while KPT report results from a pooled specification (in which each firm/month receives equal weight), they did not follow us in also reporting results from a Fama-MacBeth specification (in which each time period receives equal weight). In Table 3 we report results we obtained by both the pooled and Fama-MacBeth methods, based on quadratic estimation and coefficient standardization as recommended by KPT.[2] Like KPT, we obtain significant intercepts when quadratic terms are included and estimation is pooled, in the cases of IPOs, M&As, and dividend initiations. However, when we implement Fama-MacBeth estimation (as reported in BZ, but not reported in KPT) we obtain insignificant intercept estimates for all four corporate events. Focusing on IPOs in particular, the estimated intercept from the pooled specification with quadratic terms is -0.34% per month, while the estimated intercept from the Fama-MacBeth specification is -

[2] Here, we exclude 773 IPOs that were included in BZ. The large majority of these IPOs are non-common stocks misclassified by the SDC Platinum database, and are also excluded by KPT.

0.24% per month. Each is considerably smaller than the 0.53% per month estimate reported by KPT in Table 5 (without quadratic terms).

KPT also raise an issue quite distinct from the question of whether the regressions should be estimated with raw or normalized characteristics. They note that the data requirement we imposed in BZ that twelve months of return data be available in order to estimate beta precludes the examination of IPO returns in the months immediately following the IPO. They compute beta estimates using daily returns for a single month, which allows them to increase the number of months that can be used in the IPO analysis. Given that beta estimates are of little empirical relevance in terms of the results reported in BZ, we concur that this approach is sensible.

KPT report negative and significant intercept estimates in the expanded IPO sample when relying on linear or quadratic specifications and pooled estimation. In Table 4 we report the results obtained when we study a similarly expanded version of the IPO sample used in BZ. The results reported in Columns (3) and (4), obtained based on linear and quadratic estimation as implemented by KPT, confirm their result of economically and statistically significant intercept estimates. In columns (1) and (2) we report results obtained when characteristics are normalized as in BZ. The intercept in the linear specification is -46 basis points per month, and is statistically significant. In contrast, the intercept in the quadratic specification is almost exactly zero (negative one basis point per month). On balance, the results on Table 4 show that conclusions with regard to whether characteristics fully explain the abnormal returns to IPO firms is sensitive to whether characteristics are normalized to allow for non-linearity.

## IV. Conclusions

Expression (3) in BZ can be used to assess whether returns to event firms are abnormal after allowing for differences in firm characteristics across event and control firms. KPT concur that this approach has merit, but claim that the specific normalization of characteristics employed by BZ leads to severe econometric flaws. We show that their econometric criticisms are unfounded. They base their criticism on the results of simulations that rely on the assumptions that the true relation to be estimated is linear and that the explanatory variables are symmetric. Their simulation results are both obvious and irrelevant. While the true relation between log returns and firm characteristics is unknown, it is unlikely to be linear, due in part to the extreme skewness of firm characteristics.

We implement a bootstrap simulation in actual data, thereby incorporating the actual skewed distributions of firm characteristics and the actual, albeit unknown, relation between returns and characteristics. The results show that the methods we used in BZ provide unbiased estimates, with appropriate statistical size and strong statistical power, when implemented in actual data.

While their econometric criticisms are unfounded, KPT do provide useful robustness tests. In particular, they document that a simple linear estimation in non-normalized firm characteristics also supports the conclusion that abnormal returns are economically small in the cases of firms engaging in SEOs, M&As, and dividend initiations, but not in the case of IPOs. With regard to IPOs, our additional sensitivity tests show that the apparently abnormal returns to IPOs are also largely explained by firm characteristics when the Fama-MacBeth method is employed with quadratic terms, even when using KPT's preferred specifications.

KPT also make the useful observation that the IPO sample we employed in BZ can be expanded if betas are estimated from a single month's data. We show that conclusions as to the existence of abnormal returns following IPOs in the expanded sample differs depending on whether one assumes a linear relation between log returns and characteristics, or whether one allows for non-linearity by normalizing characteristics.

We take away three overall lessons. First, it is useful to conduct bootstrap simulations in actual data to assess the properties of a newly proposed estimation method. Second, additional robustness tests, along the lines of those provided by KPT, are informative, and keep alive the discussion as to whether returns in the months after IPOs are abnormal. Third, the evidence continues to strongly support the central BZ conclusion that firm characteristics are relevant in assessing whether the returns observed in the months after corporate events are abnormal.

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## Table 1: Skewness of firm characteristics

This table presents, for the sample employed in Bessembinder and Zhang (2013) the skewness of the event firm's characteristics and that of the difference in firm characteristics between the event firm and its size- and book-to-market (BM)-matched comparable firm. Each event firm is matched with a comparable firm based on size and BM. For mergers and acquisitions (M&As), seasoned equity offerings (SEOs), and dividend initiations, each event firm is matched with a firm whose size is between 70% and 130% of the event firm and has the closest book-to-market ratio at the end of the latest December before the event. At the end of December after initial public offering (IPO), each IPO firm is matched with a firm with the closest but greater market capitalization. Market beta for July of year $t$ to June of year $t$+1 is estimated with the monthly stock returns in years $t$-5 to $t$-1 using the market model, requiring the availability of at least 12 months of data. Size is the market capitalization at the end of the latest June. BM for July of year $t$ to June of year $t$+1 is defined as the ratio of the book value of common equity at the end of fiscal year $t$-1 to the market value of common equity at the end of December of year $t$-1. Momentum is the cumulative return over months -12 to -2. Idiosyncratic risk is the annualized standard deviation of the residual daily stock returns in the Fama and French three factor regression in month -2. Illiquidity for July of year $t$ to June of year $t$+1 is computed as the average daily ratio of absolute stock return to dollar trading volume from July of year $t$-1 to June of year $t$ divided by the market average illiquidity over the same period, as defined by Amihud (2002). Investment for July of year $t$ to June of year $t$+1 is computed as the annual change in gross property, plant, and equipment in fiscal year $t$ plus the annual change in inventory in fiscal year $t$, divided by assets at the beginning of fiscal year $t$. For each of the seven firm characteristics (beta, size, BM, momentum, illiquidity, idiosyncratic volatility, and investment), we compute the difference between the event firm and its size-and BM-matched comparable firm.

| | M&As | SEOs | IPOs | Div. init. |
|---|---|---|---|---|
| Skewness in characteristics of event firm | | | | |
| Beta | 0.68 | 0.96 | 0.70 | 0.23 |
| Size | 10.39 | 27.80 | 41.00 | 20.52 |
| BM | 22.73 | 5.76 | 20.23 | 12.18 |
| Momentum | 9.69 | 8.29 | 7.11 | 4.10 |
| Illiquidity | 57.07 | 36.28 | 75.45 | 17.95 |
| Idio. volatility | 7.24 | 4.13 | 6.13 | 4.47 |
| Investment | 103.26 | 13.80 | 128.59 | 10.26 |
| Skewness in difference in firm characteristics between event and matched firms | | | | |
| Beta | 0.01 | 0.03 | 0.36 | -0.63 |
| Size | 6.65 | -5.14 | 12.28 | 1.65 |
| BM | 15.37 | 0.44 | 10.34 | 1.81 |
| Momentum | 3.54 | 3.06 | 0.08 | -2.04 |
| Illiquidity | 51.95 | -26.86 | -2.93 | -13.85 |
| Idio. volatility | 1.78 | -0.60 | 1.78 | -1.92 |
| Investment | 94.38 | 5.14 | 114.35 | 3.33 |

## Table 2: Summary statistics regarding bootstrap simulations

In each month from January 1980 to December 2010, we divide all CRSP common stocks into 25 size portfolios, and randomly choose a pair of pseudo event firm and matching firm from each portfolio. We then run a pooled OLS regression where the dependent variable is the difference in log return (plus induced abnormal returns) between the pseudo event firm and its matching firm over the sixty months following the pseudo event, and the explanatory variables are the normalized differences in firm characteristics (with and without quadratic terms). We repeat the procedure 1,000 times. Panel A reports summary statistics regarding the 1,000 intercept estimates, in percent. Panel B reports the percentage of t-statistics of the intercept that reject the hypothesis that the intercept equals zero, at three theoretical significance levels: 1%, 5%, and 10%. Panel C reports the percentage of the resulting t-statistics on the intercept that reject the hypothesis that the intercept equals zero, at the 5% theoretical significance level, when the indicated level of annual abnormal performance is added to the returns of the pseudo event firms (a 5% annual abnormal return is about 0.42% per month). Standard errors are clustered by month.

Panel A: Intercepts estimated for random pseudo event firms (in percent)

| | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|
| Linear in Normalized Characteristics | -0.001 | 0.036 | -0.060 | -0.025 | -0.002 | 0.022 | 0.062 |
| Quadratic in Normalized Characteristics | -0.005 | 0.112 | -0.194 | -0.081 | -0.004 | 0.071 | 0.180 |

Panel B: Rejection rates for random pseudo event firms

| Two-tailed theoretical significance level (%) | 1 | | 5 | | 10 | |
|---|---|---|---|---|---|---|
| Theoretical cumulative distribution function (%) | 0.5 | 99.5 | 2.5 | 97.5 | 5 | 95 |
| Linear in Normalized Characteristics | 0.70 | 0.60 | 2.90 | 2.80 | 5.80 | 6.20 |
| Quadratic in Normalized Characteristics | 0.70 | 0.30 | 2.40 | 1.70 | 5.00 | 4.00 |

Panel C: Rejection rates for random pseudo event firms, with artificially induced performance.

| Induced annual abnormal returns (%) | -15 | -10 | -5 | 0 | 5 | 10 | 15 |
|---|---|---|---|---|---|---|---|
| Linear in Normalized Characteristics | 100 | 100 | 100 | 5.7 | 100 | 100 | 100 |
| Quadratic in Normalized Characteristics | 100 | 100 | 96.2 | 4.1 | 95 | 100 | 100 |

## Table 3: Results based on non-normalized firm characteristics

This table presents pooled OLS and Fama and MacBeth (FM) regression results for the difference in monthly log return between the event firm and its size- and book-to-market (BM)-matched comparable firm. Each event firm is matched with a comparable firm based on size and BM. For mergers and acquisitions (M&As), seasoned equity offerings (SEOs), and dividend initiations, each event firm is matched with a firm whose size is between 70% and 130% of the event firm and has the closest book-to-market ratio at the end of the latest December before the event. At the end of December after initial public offering (IPO), each IPO firm is matched with a firm with the closest but greater market capitalization. Market beta for July of year *t* to June of year *t*+1 is estimated with the monthly stock returns in years *t*-5 to *t*-1 using the market model, requiring the availability of at least 12 months of data. Size is the market capitalization at the end of the latest June. BM for July of year *t* to June of year *t*+1 is defined as the ratio of the book value of common equity at the end of fiscal year *t*-1 to the market value of common equity at the end of December of year *t*-1. Momentum is the cumulative return over months -12 to -2. Idiosyncratic risk is the annualized standard deviation of the residual daily stock returns in the Fama and French three factor regression in month -2. Illiquidity for July of year *t* to June of year *t*+1 is computed as the average daily ratio of absolute stock return to dollar trading volume from July of year *t*-1 to June of year *t* divided by the market average illiquidity over the same period, as defined by Amihud (2002). Investment for July of year *t* to June of year *t*+1 is computed as the annual change in gross property, plant, and equipment in fiscal year *t* plus the annual change in inventory in fiscal year *t*, divided by assets at the beginning of fiscal year *t*. For each of the seven firm characteristics (beta, size, BM, momentum, illiquidity, idiosyncratic volatility, and investment), we compute the difference between the event firm and its size-and BM-matched comparable firm. Wealth relative is calculated as exponential of sixty times the estimated intercept. The associated *t*-statistics are reported in the parentheses below each coefficient. Standard errors are clustered by month in pooled OLS regressions. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

| | Pooled | FM | Pooled | FM | Pooled | FM | Pooled | FM |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | SEO | | IPO | | MA | | Div. Ini. | |
| Dependent var. | Difference in log return | | | | | | | |
| ΔBeta | -0.0028** | -0.0015 | -0.0018 | -0.0011 | -0.0012 | -0.0002 | -0.0023 | -0.0031 |
| | (-2.071) | (-1.101) | (-1.302) | (-0.840) | (-0.671) | (-0.126) | (-1.559) | (-1.173) |
| Δbeta$^2$ | -0.0000 | 0.0007 | -0.0003 | -0.0003 | -0.0007** | -0.0006 | 0.0011 | 0.0017 |
| | (-0.164) | (0.900) | (-1.345) | (-0.555) | (-2.430) | (-0.775) | (1.608) | (0.830) |
| ΔSize | -0.0000 | -0.0000 | -0.0000 | 0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000* |
| | (-1.642) | (-1.561) | (-1.140) | (0.642) | (-1.067) | (-0.271) | (1.058) | (1.923) |
| ΔSize$^2$ | -0.0000 | 0.0000* | 0.0000 | -0.0000 | 0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (-0.995) | (1.675) | (0.754) | (-0.935) | (0.146) | (-0.377) | (-0.522) | (-0.247) |
| ΔBM | 0.0020 | 0.0027 | 0.0035*** | 0.0019 | 0.0027 | -0.0018 | 0.0016 | 0.0013 |
| | (1.245) | (1.076) | (3.400) | (1.375) | (1.579) | (-0.837) | (1.050) | (0.404) |
| ΔBM$^2$ | -0.0002 | -0.0007 | -0.0001*** | -0.0008 | -0.0000 | 0.0025 | 0.0000 | 0.0002 |
| | (-0.632) | (-0.273) | (-2.817) | (-0.969) | (-0.418) | (0.750) | (0.061) | (0.116) |
| ΔMomentum | 0.0041 | 0.0082*** | 0.0046* | 0.0086*** | 0.0037 | 0.0052* | 0.0029 | 0.0079** |
| | (1.507) | (3.721) | (1.652) | (3.859) | (1.252) | (1.718) | (1.238) | (2.328) |
| ΔMomentum$^2$ | 0.0000 | -0.0011 | -0.0001 | 0.0011 | -0.0002 | 0.0056 | -0.0003 | -0.0020 |
| | (0.388) | (-0.814) | (-1.248) | (1.243) | (-1.506) | (1.029) | (-0.710) | (-0.650) |
| ΔIlliquidity | 0.0000 | 0.0008 | 0.0000* | 0.0001 | 0.0000** | 0.0011 | 0.0000 | 0.0001 |
| | (1.611) | (0.812) | (1.874) | (0.919) | (1.998) | (1.547) | (1.252) | (0.683) |
| ΔIlliquidity$^2$ | -0.0000 | 0.0002 | 0.0000 | -0.0000 | -0.0000 | -0.0003 | 0.0000 | -0.0000 |
| | (-0.028) | (1.553) | (0.879) | (-1.330) | (-1.429) | (-0.473) | (0.471) | (-1.485) |
| ΔIdio. volatility | -0.3895*** | -0.4990*** | -0.2958*** | -0.4324*** | -0.3817*** | -0.5914*** | -0.2917*** | -0.5349*** |
| | (-4.834) | (-7.544) | (-4.340) | (-6.866) | (-4.241) | (-6.397) | (-3.877) | (-5.770) |
| ΔIdio. volatility$^2$ | -0.3362 | 3.6452 | 0.1802* | 1.0459 | -0.1787 | -2.1774 | -0.7724 | 3.0656 |
| | (-0.947) | (1.290) | (1.778) | (1.276) | (-0.912) | (-0.499) | (-1.057) | (0.921) |
| ΔInvestment | -0.0097*** | -0.0077* | -0.0099*** | -0.0148*** | -0.0130*** | -0.0100** | -0.0124*** | -0.0108 |
| | (-4.596) | (-1.850) | (-5.717) | (-3.924) | (-4.720) | (-2.118) | (-3.662) | (-1.413) |
| Δinvestment$^2$ | 0.0007*** | 0.0091 | -0.0001 | -0.0144 | 0.0008** | 0.0152 | 0.0016** | -0.0122 |
| | (2.669) | (1.447) | (-0.637) | (-1.433) | (2.498) | (1.401) | (1.980) | (-0.572) |
| Constant | -0.0002 | 0.0001 | -0.0034** | -0.0024 | -0.0022** | -0.0015 | 0.0035** | 0.0029 |
| | (-0.202) | (0.058) | (-2.206) | (-1.540) | (-2.250) | (-1.601) | (2.546) | (1.392) |
| | | | | | | | | |
| Cluster by date | Yes | No | Yes | No | Yes | No | Yes | No |
| Observations | 169,152 | 169,082 | 148,225 | 147,947 | 120,133 | 119,682 | 31,742 | 31,211 |
| Adjusted R2 | 0.003 | 0.111 | 0.003 | 0.096 | 0.004 | 0.141 | 0.003 | 0.258 |
| Wealth relative | 0.988 | 1.006 | 0.815 | 0.866 | 0.876 | 0.914 | 1.234 | 1.190 |

## Table 4: Replacing missing beta with beta estimated from daily stock returns for the IPO sample

This table presents the pooled OLS regression results for the difference in monthly log return between the initial public offering (IPO) firm and its size-matched comparable firm. At the end of December after IPO, each IPO firm is matched with a firm with the closest but greater market capitalization. Market beta for July of year *t* to June of year *t*+1 is estimated with the monthly stock returns in years *t*-5 to *t*-1 using the market model, requiring the availability of at least 12 months of data. If the beta is missing in a certain month after IPO, we replace it with the beta estimated using daily stock returns in the second month before that month. Size is the market capitalization at the end of the latest June. BM for July of year *t* to June of year *t*+1 is defined as the ratio of the book value of common equity at the end of fiscal year *t*-1 to the market value of common equity at the end of December of year *t*-1. Momentum is the cumulative return over months -12 to -2. Idiosyncratic risk is the annualized standard deviation of the residual daily stock returns in the Fama and French three factor regression in month -2. Illiquidity for July of year *t* to June of year *t*+1 is computed as the average daily ratio of absolute stock return to dollar trading volume from July of year *t*-1 to June of year *t* divided by the market average illiquidity over the same period, as defined by Amihud (2002). Investment for July of year *t* to June of year *t*+1 is computed as the annual change in gross property, plant, and equipment in fiscal year *t* plus the annual change in inventory in fiscal year *t*, divided by assets at the beginning of fiscal year *t*. For each of the seven firm characteristics (beta, size, BM, momentum, illiquidity, idiosyncratic volatility, and investment), we compute the difference between the event firm and its size- and BM-matched comparable firm. The results in columns (3)-(4) are based on the raw firm characteristics, while those in columns (1)-(2) are based on normalized firm characteristics. In each month, the positive differences in each firm characteristic are ranked and normalized to be its percentile ranking. All negative differences are ranked and normalized to be one minus its percentile ranking. Consequently, the normalized differences in each firm characteristics take a value from -1 to 1, with 0 corresponding to the difference in firm characteristic that is the closest to 0. Wealth relative is calculated as exponential of sixty times the estimated intercept. The associated *t*-statistics are reported in the parentheses below each coefficient. Standard errors are clustered by month. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent var. | Difference in log return | | | |
| | Normalized characteristics | | Raw characteristics | |
| ΔBeta | -0.0025 | -0.0023 | -0.0016 | -0.0015 |
| | (-0.815) | (-0.791) | (-1.399) | (-1.337) |
| Δbeta^2 | | -0.0046 | | -0.0001 |
| | | (-1.556) | | (-0.944) |
| ΔSize | 0.0024 | 0.0023 | -0.0000 | -0.0000 |
| | (1.167) | (1.105) | (-0.806) | (-0.565) |
| ΔSize^2 | | -0.0007 | | -0.0000 |
| | | (-0.287) | | (-0.011) |
| ΔBM | 0.0101*** | 0.0101*** | 0.0041*** | 0.0053*** |
| | (4.865) | (4.879) | (4.319) | (4.849) |
| ΔBM^2 | | -0.0010 | | -0.0001*** |
| | | (-0.464) | | (-3.803) |
| ΔMomentum | 0.0176*** | 0.0175*** | 0.0058** | 0.0059** |
| | (4.403) | (4.400) | (2.027) | (2.044) |
| ΔMomentum^2 | | 0.0024 | | -0.0001 |
| | | (1.068) | | (-1.476) |
| ΔIlliquidity | 0.0076*** | 0.0073*** | 0.0000** | 0.0000** |
| | (3.341) | (3.222) | (2.444) | (2.493) |
| ΔIlliquidity^2 | | 0.0061 | | 0.0000 |
| | | (1.610) | | (0.881) |
| ΔIdio. volatility | -0.0229*** | -0.0223*** | -0.3484*** | -0.3652*** |
| | (-5.743) | (-5.761) | (-4.468) | (-4.677) |
| ΔIdio. volatility^2 | | -0.0058** | | 0.2066** |
| | | (-2.155) | | (2.012) |
| ΔInvestment | -0.0126*** | -0.0115*** | -0.0000** | -0.0001*** |
| | (-6.579) | (-6.183) | (-2.266) | (-3.114) |
| Δinvestment^2 | | -0.0111*** | | 0.0000*** |
| | | (-4.441) | | (3.083) |
| Constant | -0.0046*** | -0.0001 | -0.0077*** | -0.0071*** |
| | (-2.630) | (-0.025) | (-4.287) | (-4.023) |
| | | | | |
| Cluster by date | Yes | Yes | Yes | Yes |
| Observations | 196,676 | 196,676 | 196,676 | 196,676 |
| Adjusted R2 | 0.007 | 0.007 | 0.004 | 0.004 |
| Wealth relative | 0.759 | 0.994 | 0.630 | 0.653 |