On long-run stock returns after corporate events

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Abstract

Bessembinder and Zhang (2013) show that long-run abnormal returns after major corporate events detected by the BHAR method using size and book-to-market matched control stocks can be explained by differences between event and control stocks' unsystematic and systematic characteristics. We find that their results are mainly driven by the normalization of firm characteristics, which was intended to make estimated regression coefficients comparable. Unfortunately, their normalization procedure implies incremental non-linearity and randomizes regression relations. These effects influence the slope coefficients, potentially bias alpha, and materially inflate its standard error, which causes even economically large alpha estimates to be insignificant. Revisiting their regression analyses shows 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.

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Keywords:
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Merger and acquisition
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Dividend initiation

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Abstract
Bessembinder and Zhang (2013) show that long-run abnormal returns after major corporate events detected by the BHAR method using size and book-to-market matched control stocks can be explained by differences between event and control stocks' unsystematic and systematic characteristics. We find that their results are mainly driven by the normalization of firm characteristics, which was intended to make estimated regression coefficients comparable. Unfortunately, their normalization procedure implies incremental non-linearity and randomizes regression relations. These effects influence the slope coefficients, potentially bias alpha, and materially inflate its standard error, which causes even economically large alpha estimates to be insignificant. Revisiting their regression analyses shows 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.

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Major controversy in the financial economics literature surrounds the question of whether long-run abnormal stock returns are associated with major corporate events. Based on buy-and-hold abnormal returns (BHARs), Ritter (1991) and Loughran and Ritter (1995) document post-announcement underperformance for initial public offerings (IPOs). Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) similarly report underperformance for seasoned equity offerings (SEOs). Other studies by Asquith (1983), Agarwal et al. (1992), and Mitchell and Stafford (2000) report negative long-run abnormal returns for acquiring firms in mergers and acquisitions (M&As). Billett et al. (2011) find that worse performance occurs after multiple issuances of different kinds of financial claims than after single finance events. And, Michaely et al. (1995) find positive long-run abnormal stock returns for firms initiating dividends. A common explanation for anomalous abnormal returns is overreaction as hypothesized by behavioral decision theory Kahneman and Tversky (1982).[1]

Other studies report conflicting evidence. For example, Eckbo et al. (2000) find significant underperformance for IPOs and SEOs using BHARs but insignificant results using calendar time portfolio alphas. Brav and Gombers (1997) obtain insignificant long-run results for IPOs after taking into account size and book-to-market ratios (see also Gompers and Lerner, 2003). Another study by Loughran and Vijh (1997) reports negative abnormal returns for M&As in general but positive returns for cash deals. Also, dividend initiation tests by Brav (2000) do not detect abnormal long-run returns after adjusting for size and book-to-market ratios, but further dividend tests by Boehme and Sorescu (2002) yield mixed results.

A recent paper by Bessembinder and Zhang (2013) argues that long-run abnormal returns detected by BHARs are explained by imperfect matching of event firms and control firms. They demonstrate that the event firms and their size and book-to-market

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[1] See Fama (1998) for a comprehensive discussion of long-run return anomalies and potential explanations, including market efficiency and behavioral models. In this regard, studies by Mitchell and Stafford (2000), Brav et al. (2000), Eckbo and Norli (2000), Lyandres et al. (2008), and How et al. (2011) provide different explanations for anomalous long-run stock returns after these corporate events.

matches differ in terms of unsystematic and systematic firm characteristics found earlier to be associated with returns. They propose a regression model relating abnormal returns to normalized versions of firm characteristics. With the exception of SEOs, tests of estimated intercepts (or alphas) indicate significant long-run abnormal returns for IPOs, M&As, and dividend initiations. However, their results change dramatically with the addition of squared terms for market and firm-specific characteristics in the model, as all four corporate events' alphas become insignificant. Based on these findings, they infer that long-run abnormal returns do not exist and conclude that regression results adjusted for risk reconcile previously mixed evidence.[2]

In this paper we revisit the Bessembinder and Zhang analyses. We agree that using regression techniques to account for further differences between event firms and their matches is potentially an excellent approach to control for confounding effects that otherwise may hamper detection of underlying event effects. Despite this regression advantage, it turns out that their results are mainly driven by the applied normalization procedure of the regressors. The procedure introduces incremental non-linearity in the regression, and the manner by which it is implemented randomizes regression relationships. Our results show that normalization can cause unpredictable effects on alphas and tends to inflate their standard errors, thereby making even economically relevant alphas statistically insignificant.

Upon repeating Bessembinder and Zhang regressions with samples aimed to match theirs as closely as possible for the period 1980 to 2005, our results replicate the above problems in their results, even though the test results otherwise could not exactly duplicate their findings. For M&A, SEO, and dividend initiation events, we get similar alpha estimates with normalized characteristics in the regressions. For IPOs, we find that the mean difference is highly statistically (and economically) significant which, albeit still economically significant, becomes barely statistically significant in the squared regres-

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[2] Another recent paper by Fu and Huang (2016) finds long-run abnormal returns after share repurchases and SEOs before 2002 but not after 2003. They contend that changes in the market environment account for the disappearance of long-run abnormal returns in recent years.

sions with normalized factors. More importantly, our results replicate the main problem of inflated standard errors of alphas in the Bessembinder and Zhang regression approach. When higher order terms are added to the model, the inflation symptom worsens and causes even economically meaningful alphas to become statistically insignificant. As this paper shows, these results can be attributed to the normalization of explanatory variables. When we repeat their regression analyses and other specifications using non-normalized factors, significant alphas remain significant with stable standard errors in all specifications. For these tests, the alpha associated with SEOs becomes more significant after controlling for characteristic differences. We infer that, even though event firms differ from their matches in terms of various characteristics, these differences do not necessarily explain return differences after the events. Also, the characteristic differences can work as covariates that condition out confounding return effects which mask the underlying event effect.

The next section discusses problems in normalizing regressor variables and demonstrates its effects using simulation experiments. Section 2 overviews data and methodology. Section 3 gives the empirical results of alternative long-run abnormal return test approaches. Section 4 concludes.

1 Characteristic normalization

Bessembinder and Zhang (2013) identify seven firm-specific and market-wide characteristics found in earlier literature that affect stock returns: beta, size, book-to-market, momentum, illiquidity, idiosyncratic volatility, and investments. Computing differences of these characteristics between the event firms and their matches, the authors regress monthly log-return differences between event firms and their matches on these characteristic differences. Rather than using the initial characteristic differences, they normalize them cross-sectionally, such that in each (calendar) month, the positive differences in each firm characteristic are ranked and normalized to be its percentile ranking. Negative differences are similarly normalized to their negative percentile rankings. The normalized values range from -1 to $+1$, with 0 corresponding to the difference in firm characteristic closest to 0. At first glance the normalized transformation might seem reasonable, as the dependent variable (return difference) is a relative measure but many of the explanatory variables are in absolute values. For example, size is an absolute dollar measure which in regression can cause problems as the same dollar change amount in size should have the same average return effect for small and large firms, a counter intuitive effect.

1.1 Incremental non-linearity and alpha effects

Unfortunately, normalization causes a number of severe problems. One problem is incremental non-linearity. The transformation maps the original values to empirical distribution function values (conditional on negative and positive values). As the empirical distribution function converges under fairly general conditions to its theoretical distribution function, we demonstrate the effect on the latter function. For the sake of simplicity, consider a regression with one explanatory variable. Let $y = f(x)$ be the regression function, $F_p(x)$ denote the (conditional) distribution function of x given $x > 0$, and $F_n(x)$ denote the conditional distribution function of x given $x \leq 0$. Then for positive x-values (for example), $u = F_p(x)$ corresponds to the normalized (positive) values of x. Because F_p is a distribution function, the inverse function $g = F_p^{-1}$ exists, such that $x = g(u)$. Thus, the regression in terms of u becomes $y = f(g(u))$. The degree of non-linearity in $f(g(u))$ depends on two source functions of f and g. An extreme case is when they cancel each other (in which case f would be the distribution function of x). In practice, due to the nature of the problem and choice of g, they are most likely not related and both are unknown in most cases. As such, let us approximate first f by the second order Taylor polynomial around zero, such that

$$y \approx \alpha + \beta_1 x + \beta_2 x^2, \tag{1}$$

where $\alpha = f(0) + c$, and c is the average approximation error (i.e., as in final regression estimation, the total error term will be set to average zero). In terms of the normalized variables, the approximation becomes (upon taking into account the positive values of x)

$$y \approx \alpha + \beta_1 g(u) + \beta_2 [g(u)]^2. \tag{2}$$

Again, since g is unknown, it is approximated by the second order Taylor polynomial $g(u) \approx \gamma_0 + \gamma_1 u + \gamma_2 u^2$, where γ_0 is the average approximation error as $g(0) = 0$. Using the approximation in equation (2), after rearranging terms we get

$$\begin{aligned} y &\approx \alpha + \beta_1 g(u) + \beta_2 [g(u)]^2 \\ &\approx \theta_0 + \theta_1 u + \theta_2 u^2 + \theta_3 u^3 + \theta_4 u^4. \end{aligned} \tag{3}$$

Thus, the incremental non-linearity is obvious in order to maintain the accuracy (approximately) with the initial regression. Also, equation (3) demonstrates the effect on the intercept term, which reflects the abnormal return at $u = 0$ in the final regression. The magnitude of this term may change depending on how well the approximation captures the non-linearity in $g(u)$.

[Figure 1]

To illustrate the normalization effect, we consider a simple case of linear function $f(x) = 2 + x$, such that the regression without the error term is $y = 2 + x$ with $y = 2$ at $x = 0$. Suppose that x has values $-10, -5, -3, 0, 1, 2, 5, 10, 20$ so that the y values become $-8, -3, -1, 2, 3, 4, 7, 12, 22$ (i.e., values of observations with zero error terms). Figure 1 shows the scatter plot and fitted regression lines up to a third order of the regression of y on the Bessembinder and Zhang normalized x-values $-1, -0.67, -0.33, 0, 0.20, 0.40, 0.60, 0.80, 1$ (in which the closest value to zero, here 0, has been set to zero and the rest are transformed to their corresponding percentiles for negative and positive values separately). The figure clearly shows the effect of approximation error on the intercept term. Even though the linear model otherwise does not fit the data, its intercept of 2.89 is closest to the true intercept of 2. The quadratic model produces an alpha equal to 0.49 which underestimates the true alpha. The third order model starts to capture the underlying non-linearity even though its alpha estimate of 0.96 is further away from the true alpha than the otherwise worse fitting linear specification. The bottom line is that, as this simple example demonstrates, incremental non-linearity may potentially have a strong effect on alpha estimation results, which can be even more severe if the initial model is non-linear in x.

1.2 Randomization effect

A second problem in the Bessembinder and Zhang normalization is the manner by which it is implemented within each calendar month. For example, in SEO full regressions there are 152,796 observations in Table 4 of Bessembinder and Zhang (2013) that are regrouped into 369 calendar month groups of varying sizes.[3] Thereafter the characteristics are transformed across firms independently in each subgroup (calendar month) to their within group scaled relative values from -1 to $+1$. It is obvious that this kind of group wise operation is likely to have a dramatic randomization effect on the dependence structure between the dependent variable and the explanatory variables. As an example, suppose that a characteristic difference has in May 2004 value 5 and in June 2004 value 6 with (non-scaled) ranked values 3 and 2. That is, the May characteristic value of 5 with rank 3 was the third smallest value compared to the values of other firms in May. Similarly the June value of 6 happened to be the second smallest compared to other firms in June. In this situation, the initial values are ascending but the ranked values are descending, thereby implying opposite regression effects in OLS estimation. It is obvious that this subgroup wise normalization is likely to materially increase noise in the regressions (factually, a sort of errors-in-variables problem). In Bessembinder

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[3] We do not know the exact number of calendar months as it is not reported in Bessembinder and Zhang. However, using the calendar time results in Panel E of Table 4 in their paper, we can assume that number is about the same as that in the calendar time model, i.e., 369.

and Zhang many characteristics are updated only once a year and in their Table 5 the characteristic values are kept the same for the whole event period. However, this setup does not change the situation due to regressions with pooled panel data. That is, in the regressions the data sets are technically cross-sectional on subgroup wise normalizations with the potential of distorting the original relative orderings of the values of each characteristic.

Together, the likely incremental non-linearity combined with the randomization effect due to the subgroup wise implementation of the normalization tend to materially obscure the potential regression relations and particularly affect the estimation of the key parameter alpha. As documented in forthcoming discussion, these symptoms clearly show up in Bessembinder and Zhang's regression results. For example, in Table 4 of their paper, inclusion of quadratic terms triples the alpha standard error in the IPO regression (standard errors derived from their alpha and T-values), thereby materially hampering the power of its T-test and increasing Type-II error. Our simulation and empirical results confirm these findings.

1.3 Simulation study

This section utilizes simulation analyses to demonstrate the effects of incremental non-linearity and randomization on regression intercept (alpha) estimation with cluster wise normalization. To better understand these potential effects, we vary different conditions in controlled experiments.

Because the Bessembinder-Zhang normalization is applied to each explanatory variable, the consequences of the transformation can be expected to be more pronounced as the number of variables increases. Also, due to normalization, the fraction of positive (or negative) values of each explanatory variable will affect alpha estimation. Similarly, skewness may affect the results. However, since the explanatory variables are differences of the event and control firm characteristics, their distributions can be expected to be fairly symmetric. For this reason we include in our simulations only symmetric distributions of the explanatory variables. Moreover, the number of clusters may have an impact as the explanatory variables are independently normalized within each cluster, which implies the randomization effect.

Given these considerations, our base regression is of the form

$$y = 1 + x_1 + \ldots + x_p + e, \tag{4}$$

where for simplicity the intercept and regression coefficients for p explanatory variables are set equal to one.[4] As shown in Section 1.1, the non-linearity effect of normalization is likely to be more pronounced for non-linear models. Therefore, to avoid unnecessary complications, we utilize only linear models and assume that the explanatory variables are generated independently.[5]

To focus on the main effects of normalization, we hold other things equal in different simulation experiments. For example, R-square values are fixed in all regressions. Also, the variances of the explanatory variables are equal in each experiment. Using this setup, we investigate the number of explanatory variables via estimating regressions with $p = 1$, 3, and 7 variables. In each case we estimate both linear and second order models. In the second order models the numbers of explanatory variables are 2, 6, and 14. To study the effect of the fraction of positive values for explanatory variables, we use fractions 0.70 and 0.60 that approximately match the sample values discussed later in this study. To evaluate the effects of the generating distribution of the regressors, we produce observations from uniform, triangular, normal, Laplace, and Student-T (with 5 degrees of freedom) distributions. As such, the distributions are ordered by kurtosis: the uniform and triangular distributions with respective excess kurtoses of $-6/5$ and

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[4] The OLS estimator of the intercept (alpha) is a linear combination of the sample means of the dependent and independent variables with independent variables weighted by the slope coefficients (i.e., equal weighting).

[5] The Bessembinder and Zhang factors appear to be very low correlated. For example, for our SEO sample in Section 2, the highest correlation is 0.17 and most are well below 0.1 in absolute value terms.

$-3/5$ have lower kurtoses than the normal distribution, and the Laplace and Student $T(5)$ distributions with excess kurtoses of 3 and 6 have higher kurtoses. Finally, to examine the effect of the number of clusters on the regression intercept term, we use three groupings of 20, 50, and 100 equal-sized clusters.

Altogether, our simulations design (i.e., conditions under which data are generated) is $3 \times 2 \times 5 \times 3$ of (3 regressions: each with linear and quadratic specifications) × (2 positive fractions of explanatory variable observations) × (5 distributions) × (3 groupings), or 90 dimensional. In each of 5,000 simulation rounds, we generate $N = 5{,}000$ observations and estimate the regressions. The standard deviation of the explanatory variables are all fixed at $\sigma_x = 3$, and other parameters are calibrated to satisfy the probability of positive values (i.e, 0.70 and 0.60).

While not relevant to demonstrating the effects of the Bessembinder and Zhang normalization, we introduce intra-class correlations of the observations within each cluster and estimate cross-sectional correlation robust standard errors via the clustering method of Cameron et al. (2011). Correlation purely inflates the standard errors independent of the normalization effect and therefore introduces noise that masks the regression effects of interest. We account for intra-class correlations by modeling the error term e in regression (4) using the following random component model

$$e_{it} = \eta_t + \epsilon_{it}, \tag{5}$$

where $\eta_t \sim N(0, \sigma_\eta^2)$ and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ are independent, $t = 1, \ldots, K$ with K the number of clusters (here $K = 20$, 50, or 100), and $i = 1, \ldots, n$ with $n = N/K$ the number of observations in the equal-sized cluster (see Petersen, 2009). This procedure implies within cluster correlation of $\rho_e = \sigma_\eta^2/(\sigma_\eta^2 + \sigma_\epsilon^2)$ in the error terms. Utilizing equation (4) in Kolari and Pynnönen (2010), we fix the component variances of η_t and ϵ_{it} in equation (5) such that inflation factor $\sqrt{1 + (n-1)\rho_e}$ of the standard error equals 2 in each cluster size when estimating a model with only the intercept term. Because our focus is on the intercept and not the slope coefficients of the regressors, the explanatory variables are allowed to be independently distributed, which implies that the standard errors of the slope coefficients are not affected by the cluster wise intra-class correlation of the error term (see Petersen, 2009). By eliminating unrelated noise effects, this procedure again serves the purpose of isolating the potential effects of normalization.

Appendix A.1 Table A.1 reports the alphas and their cluster robust standard errors from the simulations. The rows alpha(x) and alpha(x, x^2) report average alpha estimates from 5,000 simulation samples for the linear and quadratic regressions, where the quadratic regressions include linear and quadratic terms of the original regressors. Similarly, rows alpha(u) and alpha(u, u^2) report average alphas from regressions in which the explanatory variables are replaced by their Bessembinder and Zhang (2013) normalized transforms, with normalizations applied over the whole sample period. We include these normalizations to measure the randomization effect of the cluster wise normalization on the standard errors discussed in Section 1.2. Comparing these standard errors reported in rows alpha(u; clust) and alpha(u, u^2; clust) with the respective alpha(u) and alpha(u, u^2) standard errors shows the effect.

The simulation results in Table A.1 are easily summarized. Normalization tends to bias the alpha estimates which is partially mitigated by second order terms in some cases. The bias depends on the parent distribution of the explanatory variables and how far the distribution is located from that of the symmetrically distributed case about zero (as measured by the probability of positive or negative explanatory variable values). The standard errors are relatively insensitive to the parent distribution and the number of clusters but increase materially due to inclusion of the quadratic terms of the explanatory variables in the normalized models as the number of explanatory variables grows. For example, in Panel A of Table A.1 for the case of 50 clusters and one regressor that is Student-T distributed, the average standard error of alpha(u; clust) estimated with one explanatory variable is 0.053, and after inclusion of the quadratic term, the average standard error increases only slightly to 0.055, or 3.8%. By contrast, in the case of seven explanatory variables, the average standard errors increase from 0.153 to 0.242, or 58.2%. The corresponding change in regressions with non-normalized x-variables is only 7.8% from 0.128 to 0.138. The major reason for this difference is that the second order terms of the normalization are not able to capture the incremental non-linearity of the transformation, thereby accumulating into the standard errors of alphas as the number of explanatory variables grows. This effect becomes more apparent by comparing standard errors of alphas in non-normalized and normalized regressions. In the above case of seven explanatory variables, the standard errors increase from the non-normalized case of 0.128 to 0.153, or 19.5%, in the linear linear regressions, and from 0.138 to 0.242, or 75.4%, thereby substantially decreasing the power of the related T-test and increasing Type II error. Finally, the extra inflation effect on standard errors due to the cluster wise normalization seems to remain relatively small, i.e., typically 10 to 20 percentage points in the linear case and only 5 to 6 percentage points in the quadratic case.[6]

While the inflation effect on the standard errors of alpha estimates appears to be mainly driven by the number of explanatory variables, biasing effects on alphas appear to depend on the parent distributions and how much their locations deviate from zero. For example, in Panel A of Table A.1 for the normal case, the linear model alphas, or alpha(u; clust), with seven regressors range from 4.553 to 4.825 and in Panel B from 2.748 to 2.867, thus severely overestimating the true alpha of 1.0. Inclusion of the quadratic terms reduces the bias, as Panel A alphas range from 1.497 to 1.575 and Panel B from 1.133 to 1.174. In the case of Laplace distributed explanatory variables, the situation improves in the linear case but gets worse in the quadratic case. In Panel A the average alphas in the linear case range from 1.492 to 1.760 compared to the quadratic case from -0.424 to -0.362. The corresponding ranges in Panel B are from 0.947 to 1.067, i.e., virtually unbiased for the linear models, whereas for quadratic specifications they range

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[6] For example, referring to the Student-T distribution with 50 clusters in Panel A of Table A.1 for seven regressors, the standard error for alpha(x) is 0.128 versus 0.137 for alpha(u), or 7% higher, whereas for alpha(u; clustering) it is 0.153, or 19.5% higher), such that normalizing cluster wise inflates the standard error an additional 12.5 percentage points. Similar computations for the quadratic regressions show a 5.8 percentage point additional inflation effect in the cluster wise normalization.

from -0.066 to -0.040, which are severely biased. On the other hand, for Student-T distributed explanatory variables the results in Panel A indicate that the linear specification produces positive biases in alphas ranging from 1.280 to 3.233, whereas the quadratic specification produces increasingly downward biased alphas ranging from 0.961 down to 0.670 with the number of explanatory variables. Similar results are obtained in Panel B of Table A.1.

Overall, normalization increases the standard errors of the alpha estimates and can cause unpredictable biasing effects depending on the distributional properties of the explanatory variables. Inflated standard errors are mainly due to the incremental nonlinearity of the normalization, which in most cases is not adequately captured by inclusion of second order terms of the normalized variables. With the exception that the randomization effect is less pronounced than expected, these results corroborate earlier theoretical discussion in the section. We next empirically demonstrate these concerns by revisiting the Bessembinder and Zhang (2013) study with sample data closely matching theirs.

2 Data and methodology

In this section we overview sample selection and the Bessembinder and Zhang regression. The sample selection aims to match that of Bessembinder and Zhang (2013) as closely as possible covering events in the period from 1980 to 2005 with the last 5-year post event return period ending 2010.

2.1 Sample selection

The M&A sample consists of completed U.S. mergers and acquisitions in the Thomson ONE (SDC) database between 1980 and 2005 with transactions value of $5 million or more. Following Betton et al. (2008), we apply two filters: (1) the acquisition takes the form of a merger (M), majority interest (AM), remaining interest (AR), or partial interest (AP); and (2) the acquisition is a control bid wherein the acquirer owns at least 50% of the target after the deal. Also, we require that the relative size of the deal (viz., transaction size divided by the market value of the acquirer) to be greater than 5% to eliminate small deals. In total, we have 4,169 acquisitions.

We select a control firm for each firm by matching size and book-to-market ratio (BM) characteristics on CRSP and Compustat. Following Eckbo et al. (2007) and Bessembinder and Zhang (2013), for each M&A deal completion, matched firms have closest BM among firms with firm size between 70% and 130% of the bidder firm. We eliminate matching firms that are in our sample of bidders within five years before the event date.

Firm size (market capitalization) is calculated at the end of December prior to the M&A deal completion date. BM is the ratio of book equity to market equity at the end of year $t-1$. Following Fama and French (1993), book equity is defined as the Compustat book value of stockholders equity, plus balance sheet deferred taxes and investment tax credits (if available), minus the book value of preferred stock. Depending on availability, the redemption, liquidation, or par value (in that order) is used to estimate the value of preferred stock.

Table 1 shows the distribution of acquisitions in our sample period. Before 1994 the number of transactions ranged from only 1 in 1982 to 179 in 1993. Transactions peaked in the period 1996–2000 ranging from 297 to 371. Subsequently, the number of deals declined to a low of 146 in 2002 and then climbed to 198 in 2005.

[Table 1]

The SEO sample consists of completed U.S. SEOs in the Thomson ONE (SDC) database between 1980 and 2005, excluding American Depository Receipts, Global Depository Receipts, and unit offerings. Financial and utility firms are excluded also. The procedure for selecting matching firms is similar to the M&A sample. There are 5,226 SEO events. Table 1 shows the distribution of the SEOs over time.

The IPO sample includes all completed U.S. initial public offerings (IPOs) in the

Thomson ONE (SDC) database between 1980 and 2005, excluding Real Estate Investment Trusts, closed-end funds, American Depository Receipts, unit trust offerings and units.[7] We select matching firms among the firms having CRSP data using market capitalization. Following Loughran and Ritter (2000), for each IPO event, the matched firm has the closest but greater market capitalization at the end of December following the IPO. Matching firms must have been publicly traded for more than 5 years. There are 7,347 IPO events. Table 1 shows that the number of IPOs increased in the 1990s and thereafter generally declined.[8]

The dividend initiations (DIV) sample includes cash dividend initiations in the CRSP database between 1980 and 2005. Following Boehme and Sorescu (2002) and Bessembinder and Zhang (2013), we apply the criteria that common stocks are listed on the NYSE, NYSE MKT (AMEX), or NASDAQ (viz., share code 10 or 11 and exchange code 1, 2 or 3), stocks have been included in the CRSP for more than two years, dividends are ordinary cash (U.S. dollars), and they are paid regularly[9]. We apply the same matching procedures as for M&A and SEO samples. There are 882 dividend initiations ranging from 12 in 1980 to 115 in 2003.

We recognize that the numbers of event firms for different corporate actions in our paper differ to some degree from those of Bessembinder and Zhang (2013). Our sample sizes for SEOs, M&As, and dividend initiations are quite similar to theirs (i.e., 5,226 firms here versus 5,131 firms, 4,169 firms here versus 3,972 firms, and 882 firms here versus 887 firms, respectively). A nominal difference occurs for IPOs, for which Bessembinder and Zhang have 8,966 firms compared to 7,347 cases here, both of which are large samples.[10] Finally, because 103 M&As, 141 SEOs, and 9 DIVs miss all event period returns, in

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[7] Unit IPOs are bundles of common stocks and warrants Schultz (1993). There are no material changes in our conclusions if we include units. There are 738 units between 1980 and 2005. We also excluded stocks that began trading on CRSP at dates far distant from the indicated IPO dates from SDC (60 days).

[8] Both Doidge et al. (2013) and Gao et al. (2013) document a decline of IPOs after 2000 also.

[9] The frequency of dividends is monthly, quarterly, semiannual, annual, or unspecified (viz., third digit of distribution code is 1, 2, 3, 4 or 5). As noted by Boehme and Sorescu (2002), unspecified frequencies are mostly quarterly.

[10] In addition to our sample, we used the original sample from Bessembinder and Zhang (2013) also.

subsequent analyses the maximum number of events for these cases are 4,066, 5,085, and 873, respectively.

2.2 Bessembinder and Zhang model

Bessembinder and Zhang (2013) contend that the BHAR matched control firm procedure does not fully control firm differences that can affect long-run abnormal returns. They point out that the continuously compounded abnormal return between an event and matched control firm, or $\texttt{CCAR}_{it} = \log(1+R_{it}) - \log(1+R^c_{it})$, in which R_{it} and R^c_{it} are the simple returns of the event and matched control firm, respectively, corresponds to a log wealth relative as defined by Loughran and Ritter (1995).[11] In an effort to better control for differences between the event firms and their matches in testing long-run abnormal returns, the authors specify regression model

$$\begin{aligned}\texttt{CCAR}_{it} = \alpha + \beta_1 \Delta\texttt{beta}_{it} + \beta_2 \Delta\texttt{size}_{it} + \beta_3 \Delta\texttt{BM}_{it} \\ + \beta_4 \Delta\texttt{mom}_{it} + \beta_5 \Delta\texttt{illiq}_{it} + \beta_6 \Delta\texttt{isv}_{it} + \beta_7 \Delta\texttt{inv}_{it} + e_{it},\end{aligned} \tag{6}$$

where Δ denotes the monthly difference between event firm and matching firm characteristics, `beta` for July of year t to June of year $t+1$ is estimated from the market model using monthly stock returns during years $t-5$ to $t-1$,[12] `size` is the market

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[11] The authors argue that testing for zero CCAR is equivalent to testing zero BHAR or unity of the wealth ratio. However, this claim may not hold. BHAR leads to portfolio testing as simple returns aggregate to portfolios, whereas it is well known that log-returns do not aggregate to portfolio returns. In this regard, Barber and Lyon (1997, Sec. 2.3) do not recommend the use of continuously compounded returns for analyzing long-run return performance. In this respect, we agree with Bessembinder and Zhang that log-returns are useful in assessing long-run return performance due to their more attractive statistical properties, which lead to more reliable tools for detecting potential event implied changes in the return generating process. Subsequently, economic consequences can be evaluated with relevant return measures and portfolio strategy arguments.

[12] For each stock it is required that there are a minimum of 12 months of returns (according to personal communication with Bessembinder and Zhang). Because IPOs do not have pre-event returns, this restriction results in a loss of 18 to 29 or more months from the beginning of the event period. A minimum of 18 months are lost if January of year $t-1$ is the event month. In the other extreme, 29 or more months are lost if the first available monthly return is in February (i.e., if this is also the event month and all subsequent returns are available, 29 months are lost, otherwise more). In this case the 23 months in years $t-2$ and $t-1$ are used to compute the beta for July of year t to June of year $t+1$.

equity at the end of the latest June, `BM` for July of year t to June of year $t+1$ is the book value of the common equity to the market value of common equity at the end of fiscal year $t-1$, `mom` is momentum computed using cumulative returns for months -12 to -2, `illiq` is illiquidity in July of year t to June of year $t+1$ proxied by the average ratio of daily absolute stock return to dollar trading volume from July of year $t-1$ to June of year t (see Amihud, 2002),[13] `isv` is idiosyncratic volatility as measured by the annualized standard deviation of the residuals obtained in a Fama and French three-factor regression using daily returns in month -2, and `inv` is capital investment in July of year t to June of year $t+1$ based on the annual change in gross property, plant, and equipment in fiscal year t divided by assets at the beginning of fiscal year t. As discussed in Section 1, in an effort to make estimated slope coefficients in regression (6) comparable, Bessembinder and Zhang normalize the characteristic differences by their monthly cross-sectional procedure to positive and negative percentile ranks that range from -1 to $+1$.

3 Empirical results

Tables 2 and 3 report the estimated regression coefficients based on equation (6) with normalized factors. In the bottom portion of these tables, F-tests of the joint significance of the squared terms are shown, in addition to mean CCARs (i.e., inital alphas from regressions without factors) and their cross-sectional correlation adjusted T-values. The analyses include all stocks for which regressors and returns are available for the 60-month holding period or the month of delisting, whichever occurred first. Thus, these results reflect average monthly abnormal returns for firms surviving up to 60 months. Tables 4 and 5 replicate regressions in Tables 2 and 3 with non-normalized factors. The

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[13] Following Amihud (2002), average market illiquidity in the denominator is calculated using illiquidity of all stocks satisfying the following conditions: (1) the stock has return and volume data for more than 200 days (from July of year $t-1$ to June of year t), (2) the stock price is greater than \$5, (3) the stock has data on market capitalization available, and (4) illiquidity outliers are eliminated at the highest or lowest 1%.

reported regression slope coefficients are, however, scaled by standard deviations of the corresponding factors to make the coefficients comparable. Unlike Bessembinder and Zhang's normalization, our procedure does not affect alphas, goodness-of-fit statistics of the regressions, nor relative magnitudes of factor values. Thus, the scaling is purely technical with the purpose of putting the slope coefficients on equal footing, such that each of them reflects the return effect of a one standard deviation change in the respective characteristic difference.

[Tables 2 and 3]

Figures 2 to 5 plot firm characteristics used in the regressions. Pre- and post-event median values of the characteristics are shown for the event and matching control firms.[14] These figures are consistent with those of Bessembinder and Zhang (2013, Figures 1–4) and confirm their observation that event firms tend to differ from their matches in terms of these characteristics, thereby motivating them to investigate whether potential abnormal returns are explained by these differences.

[Figures 2, 4, 3, and 5]

Regarding M&As in Figure 2, the most obvious differences between event and matching control firms among regressor factors are investment activity around the event month as well as disparities in size and book-to-market values after the event month. Given the nature of the the event, these differences are expected. Focusing initially on the linear and second order models in Table 2 for M&As comparable to those reported in Bessembinder and Zhang (2013, Panel C of Table 4), it is notable that in our case the second order (i.e., squared) terms are neither individually nor jointly significant. In their study, the squared term of beta is significant at the 5% level, and the squared term of the idiosyncratic volatility is borderline significant at the 10% level. In our case inclusion of these terms inflates the standard error of alpha from 0.097 to 0.233 in Table 2 or 140%. In their regression results the standard error is inflated by 90%. However, unlike their results, our regressions indicate insignificant alphas even without the squared terms. The

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[14] Since pre-event values are not available in the IPO sample, Figure 4 shows only post-event values.

mean CCAR in the regression sample panel of Table 2 corresponds to alpha without any regressors, i.e., model $\texttt{CCAR} = \alpha + e$. This alpha estimate is significant at the 5% level. The mean CCAR results in the full sample panel contain all available observations and correspond to the alpha result in Column 1 of Table 4's Panel C in Bessembinder and Zhang. Even though we did our best to match our sample to theirs, our results in the full sample panel of Table 2 indicate insignificant alpha (and even BHARs indicate insignificant abnormal returns), whereas Bessembinder and Zhang's alpha is highly significant.

It is true that in their case the alpha estimates decrease with the addition of squared terms to the linear model. However, as discussed in Section 1.1 and demonstrated by Figure 1, non-linearity caused by normalization likely requires higher order terms to adequately capture the implied extra non-linearity. Indeed, enhancing in our case the M&A regression model with third powers of the explanatory variables reveals that third order terms are jointly the only significant factors in the regression (i.e., the F-test p value is 0.020 in Table 2). Among the individual coefficients, there are only two significant regressors: the borderline significant first order term of momentum and the third order term of idiosyncratic volatility. As noted above, even though alphas are insignificant in each specification and thus differ from those of Bessembinder and Zhang, the inflation effect on standard errors is similar to their results. In view of the ongoing controversy in the literature discussed in the introduction, these conflicting results on the significance of alphas or BHARs suggest that further methodological research is needed to better understand ambiguous long-run abnormal return results.

The SEO columns in Table 2 provide CCAR regression results. Unlike other corporate events, estimated alphas are insignificant in both samples with or without squared terms. Again the squared terms of the normalized factors are jointly insignificant. These results for the linear and squared term regressions are consistent with those in Bessembinder and Zhang. Inclusion of third order terms does not change the significance of the alpha estimate. However, the standard error of alpha estimates become strongly inflated by almost doubling in the non-linear models compared to the linear model. Finally, consistent with our discussion in Section 1.1, third order terms are highly significant. With these terms, the magnitude of alpha increases substantially relative to the linear model and becomes economically significant with an abnormal return of −0.259 percentage points per month or approximately −3.1 percentage points per year. However, due to inflated standard errors, it is still far from being statistically significant at any conventional level.

Table 3 reports the IPO regression results. In the full sample the average BHAR of −28.4 percentage points is highly significant. In the regression sample the BHAR is considerably smaller at −7.1 percentage points but still significant at the 5% level. Consistent with Bessembinder and Zhang (2013, Panel B of Table 4), alpha is highly significant in the linear regression of CCARs on the characteristic differences. Similar to Bessembinder and Zhang, the significance of alpha drops dramatically after inclusion of the squared terms. In their case the alpha estimate becomes statistically insignificant. In our case, even though there is little change in alpha from −0.547 in the linear case to −0.495 in the quadratic regression, the T-value drops substantially from highly significant at −3.71 to barely 10% significant at −1.87. The reason for the drop in significance is the 80.3% inflated standard error in the quadratic regression. Inclusion of the third order terms does not change the situation. It is notable that in all specifications alphas are economically highly significant even at the lowest estimate of −0.495 percentage points per month (i.e., −5.94 percentage points per year or −29.7 percentage points in 5-years). Finally, similar to M&As and SEOs, the table shows that the second order terms are jointly statistically insignificant, whereas the linear and third order terms are highly significant.

It turns out that the weak significance of alpha in the quadratic regression with Bessembinder and Zhang normalized characteristics in Table 3 can be attributed to the large number of lost months from the beginning of the event period due to the way beta is estimated (see footnote 12). Since beta is not statistically significant, we dropped it and its squared term from the equations. Results are reported in Table A.2 in Appendix A.2. The number of months increases from 108,005 in Table 3 to 151,944 in Table A.2. Also, the number of firms increases from 3,877 in Table 3 to 4,616 in Table A.2. More importantly, as seen from the first three columns of Table A.2, alphas become both economically and statistically highly significant in all specifications with the Bessembinder and Zhang normalized regressors. To confirm the lost-months effect, we estimated betas (similar to idiosyncratic volatility) from daily returns in month $t-2$, which avoids losing observations due to beta. Table A.3 reports the results that in terms of alpha are virtually identical to those in Table A.2, i.e., highly economically and statistically significant alphas in all specifications. To further illustrate the lost-months effect, Table A.4 in Appendix A.2 repeats Table A.3 for the months available in Table 3 of the main text. Again, similar to Table 3, alpha in the quadratic regression with Bessembinder and Zhang normalized regressors loses its significance by becoming as in Table 3 only weakly significant at the 10% level with T-value -1.71. We infer that dropping 18 to 29 months of post-IPO returns due to the Bessembinder and Zhang approach to beta estimation omitted a considerable amount of the market reaction to IPOs. Adding back most of these months results in significant abnormal returns even with their normalized characteristic differences.

The situation is quite different with the non-normalized characteristics differences as regressors. Whichever the specification, alphas are highly economically and statistically significant (see the first three columns in Table 5 as well as the last three columns in Tables A.2, A.3, and A.4). Thus, even exclusion of a substantial number of event period months from the beginning of the period does not eliminate alpha. Altogether, these empirical results strongly suggest that the issues related to the Bessembinder and Zhang normalization tend to produce outcomes for alphas that are highly sample specific, while results from the models with non-normalized characteristics are far more consistent.[15] On the basis of these findings, we do not find any reliable empirical evidence

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[15] Our results are robust if we include units in our sample or if we use Bessembinder and Zhang (2013)

that firm characteristic differences would explain IPO post-event underperformance. Instead, our IPO findings support those of many earlier studies that have documented material underperformance of IPOs (for example, see Betton et al., 2008, among others). In contradiction to Bessembinder and Zhang (2013), our further analyses suggest that outcomes from the regression method with normalized factors may be highly sample specific, thereby hampering the reliability of inferences.

Results for dividend initiations (DIVs) in the last three columns of Table 3 are similar to those for M&As and SEOs, with the exception that in the enhanced models both second and third order terms are jointly significant. Interestingly, estimated alphas in the second and third order models are economically large and negative but far from statistical significance (viz., -0.444 and -0.378 percentage points per month with T-values of -1.24 and -1.04, respectively). The addition of higher order terms at worst almost triples the standard errors of alphas rendering them insignificant even in a case with an economically significant estimate of -0.444 percentage points per month, or about -5.3 percentage points per year.

Due to problems of cross-sectional normalization of explanatory variables in panel data analyses, we repeat the regression analyses using non-normalized factors. As shown in Tables 4 and 5, particularly with respect to the inclusion of squared terms, the results are quite different from those with normalized factors. Regardless of whether or not second order terms are included, with the exception of DIVs, all estimated alphas are highly significant. Notably, the standard errors of alphas remain virtually unchanged across different model choices. The SEO results are interesting, as controlling for characteristic differences causes alpha to become both economically and statistically more significant. This result implies that, while the average returns of the event firms and their matches do not differ discernibly in terms of BHARs, after controlling for various firm characteristics, they tend to differ. The return averages without the controls reflect unconditional mean behavior. Regressions with controls indicate conditional average return behavior

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original sample. Additional tables are available upon request.

after accounting for the characteristics. As such, an insignificant unconditional alpha suggests that confounding effects mask the event effect which becomes revealed after conditioning with the characteristic differences. In sum, controlling for important factors like those identified by Bessembinder and Zhang (2013) may reveal hidden event effects instead of explaining them away. The conflicting results documented here show that further research is needed to develop best practices for utilizing various firm and other characteristics as controls in CCAR regressions.

[Tables 4 and 5]

4 Conclusions

This paper addressed problems of transforming independent variables in regressions to their percentile ranks by means of subgroup wise normalization. Recent work by Bessembinder and Zhang (2013) applied this type of normalization to help explain observed return differences between event and control firms around major corporate events. We showed that normalization tends to increase non-linearity in the regression and, if the transformation is implemented subgroup wise, the regression relations tend to become randomized. In combination, these effects can blur regression results and render even economically large unexplained return differences (alphas) statistically insignificant.

We demonstrated these econometric problems using both simulation experiments and empirical analyses that replicate the Bessembinder and Zhang study with similar data and regression methods. Simulations confirmed the inflation effects on the standard errors of alphas and indicated that the resulting alphas themselves may be biased depending on the distributions of the original explanatory variables. Empirical replications of their analyses for mergers and acquisitions (M&As), initial public offerings (IPOs), seasoned public offerings (SEOs), and dividend initiations (DIVs) confirmed our main concerns. The normalization of firm characteristics dramatically decreased the precision of estimating the key parameter alpha. The instability of estimating alpha using normalized characteristics was evident when the results were compared to those using original characteristics. In most of the empirical replications with normalized characteristics, the squared characteristics in the enhanced models similar to Bessembinder and Zhang were not statistically significant, and the standard errors of alphas with the normalized characteristics became highly inflated after the inclusion of squared terms. The latter inflation problem did not occur when the original characteristics were used, such that most of the alphas remained highly statistically significant with squared terms.

In conclusion, we found little reliable support for explaining long-run abnormal returns with firm characteristics. In spite of these drawbacks, we believe that regression approaches can be helpful in characterizing long-run return patterns after major corporate events. Further research is recommended to identify reliable factors and best practices to capture risk adjustment in abnormal returns and thereby gain a better understanding of long-run stock return patterns.

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Year	M&A	SEO	IPO	DIV
1980	5	116	93	29
1981	9	129	239	24
1982	1	148	85	12
1983	2	348	529	18
1984	27	97	230	25
1985	97	137	241	21
1986	110	201	504	25
1987	121	152	353	27
1988	94	71	140	47
1989	107	99	120	47
1990	71	99	121	39
1991	101	201	283	27
1992	141	197	395	29
1993	179	253	503	29
1994	246	214	393	42
1995	313	283	446	56
1996	310	332	663	23
1997	368	305	445	25
1998	371	214	283	13
1999	294	215	447	26
2000	297	241	327	13
2001	206	233	69	16
2002	146	211	63	27
2003	175	227	66	115
2004	180	290	161	76
2005	198	213	148	51
Total	4,169	5,226	7,347	882

Table 1: Number of M&As, SEOs, IPOs, and dividend initiations (DIV) in different years.

Description: The M&A sample consists of completed U.S. mergers and acquisitions in the Thomson ONE (SDC) database with transaction values of $5 million or more. Acquisitions must take the form of a merger (SDC deal form M), acquisition of majority interest (AM), acquisition of remaining interest (AR), or acquisition of partial interest (AP). The acquisition must be a control bid, in which the acquirer owns at least 50% of the target after the deal. The relative size of the deal (transaction size divided by the market value of the bidder firm before the completion) must be greater than 5%. The IPO sample excludes Real Estate Investment Trusts, closed-end funds, American Depository Receipts, unit trust offerings and units. The SEO sample excludes American Depository Receipts, Global Depository Receipts, unit offerings, and financial and utility firms. Lastly, the dividend initiations (DIV) sample includes common stocks listed on the NYSE, NYSE MKT (AMEX), or NASDAQ with CRSP data available for more than two years. Dividends are ordinary cash in dollars that are paid regularly.

	M&A			SEO		
	Linear	2nd order	3rd order	Linear	2nd order	3rd order
$\Delta\texttt{beta}$	−0.216	−0.199	0.098	−0.206	−0.213	0.204
	(−0.77)	(−0.72)	(0.34)	(−0.97)	(−1.01)	(0.73)
$(\Delta\texttt{beta})^2$		−0.407	−0.390		0.106	0.156
		(−1.54)	(−1.52)		(0.50)	(0.73)
$(\Delta\texttt{beta})^3$			−0.521			−0.719
			(−0.98)			(−1.60)
$\Delta\texttt{size}$	−0.126	−0.129	−0.301	0.068	0.096	−0.064
	(−0.66)	(−0.67)	(−0.73)	(0.45)	(0.63)	(−0.20)
$(\Delta\texttt{size})^2$		−0.300	−0.330		−0.254	−0.250
		(−1.07)	(−1.17)		(−1.08)	(−1.05)
$(\Delta\texttt{size})^3$			0.181			0.182
			(0.34)			(0.46)
$\Delta\texttt{BM}$	0.040	0.028	−0.081	0.158	0.147	0.240
	(0.26)	(0.18)	(−0.26)	(1.15)	(1.08)	(0.96)
$(\Delta\texttt{BM})^2$		0.351	0.364		0.454^b	0.443^b
		(1.46)	(1.52)		(2.03)	(1.98)
$(\Delta\texttt{BM})^3$			0.140			−0.185
			(0.28)			(−0.45)
$\Delta\texttt{mom}$	1.255^c	1.265^c	0.855^b	0.855^c	0.866^c	0.611^b
	(3.38)	(3.40)	(2.09)	(3.79)	(3.69)	(2.08)
$(\Delta\texttt{mom})^2$		−0.181	−0.181		0.236	0.261
		(−0.78)	(−0.78)		(0.73)	(0.79)
$(\Delta\texttt{mom})^3$			0.599			0.401
			(1.05)			(0.73)
$\Delta\texttt{illiq}$	0.733^c	0.740^c	0.398	0.600^c	0.623^c	0.323
	(3.72)	(3.75)	(0.94)	(3.82)	(3.98)	(1.11)
$(\Delta\texttt{illiq})^2$		−0.183	−0.154		−0.239	−0.180
		(−0.54)	(−0.46)		(−0.81)	(−0.61)
$(\Delta\texttt{illiq})^3$			0.605			0.537
			(0.96)			(1.20)
$\Delta\texttt{isv}$	$−1.484^c$	$−1.478^c$	−0.085	$−1.689^c$	$−1.706^c$	$−0.837^c$
	(−4.51)	(−4.49)	(−0.24)	(−6.36)	(−6.74)	(−2.87)
$(\Delta\texttt{isv})^2$		−0.074	−0.026		−0.038	0.001
		(−0.24)	(−0.08)		(−0.16)	(0.00)
$(\Delta\texttt{isv})^3$			$−2.392^c$			$−1.516^c$
			(−3.52)			(−3.22)
$\Delta\texttt{inv}$	0.088	0.103	0.131	0.295^b	0.306^b	0.211
	(0.49)	(0.57)	(0.41)	(2.04)	(2.10)	(0.88)
$(\Delta\texttt{inv})^2$		0.028	0.049		0.010	−0.003
		(0.11)	(0.19)		(0.05)	(−0.02)
$(\Delta\texttt{inv})^3$			−0.123			0.113
			(−0.24)			(0.30)
$\hat{\alpha}$	−0.102	0.164	0.134	−0.116	−0.211	−0.259
	(−1.05)	(0.71)	(0.57)	(−1.19)	(−1.17)	(−1.43)
Std. error ($\hat{\alpha}$)	[0.097]	[0.233]	[0.235]	[0.098]	[0.180]	[0.182]
Adjusted R^2	0.003	0.003	0.004	0.003	0.003	0.003
F for linear terms	6.78	6.66	1.05	11.29	11.55	2.17
p-value	0.000	0.000	0.396	0.000	0.000	0.036
F for 2nd order terms		0.83	0.87		0.80	0.85
p-value		0.566	0.534		0.590	0.550
F for 3rd order terms			2.41			2.34
p-value			0.020			0.024
		Samples			Samples	
		Regression	Full		Regression	Full
Mean(CCAR)		$−0.247^b$	−0.091		$−0.188^a$	$−0.215^a$
T-value		−2.28	−1.12		−1.77	−1.88
Std. Error (mean)		0.109	0.081		0.106	0.115
BHAR		−0.041	−1.432		−0.811	−4.309
t-bhar		0.00	−0.25		−0.20	−1.23
N clusters		365	371		372	372
N months		99,769	171,935		164,255	221,840
N firms		2,604	4,066		4,205	5,085

Table 2: Normalized firm characteristics and long-run abnormal returns for M&As and SEOs.

Description: The table presents OLS regressions of monthly continuously compounded abnormal returns (CCARs) for M&As and SEOs based on normalized differences of firm and market characteristics specified by Bessembinder and Zhang (2013). The length of the event period for each stock is up to 60 months or the time of delisting, whichever comes first. The T-ratios of the regression coefficients are in parentheses, and standard errors of alphas are in brackets. The middle portion of the table reports F-statistics and their p-values separately for the joint significance of the linear, squared, and cubic terms in the regressions. The bottom portion reports mean CCARs and their T-values as well as number of clusters over which the cross-sectional correlation robust standard errors by Cameron et al. (2011) (see also Petersen, 2009) are computed. All the T-values, standard errors of alphas, and F-values in the table are based on these cross-sectional correlation robust standard error computations. The mean CCARs should be interpreted as the average monthly abnormal returns for stocks with event periods up to 60 months rather than 5-year average monthly abnormal returns. It is notable that the number of clusters (N clusters) reported in the bottom portion is the effective number of observations for inferences instead of the considerably higher number of months (N months) or number of firms (N firms) reported in the last two rows at the bottom. Similar to Bessembinder and Zhang (2013), it is notable that the number of firms in the regression samples are considerably smaller than in the full samples due to limited data availability for the explanatory variables. Superscripts represent significance levels for two-tailed T-tests as follows: $a = 0.10$, $b = 0.05$, and $c = 0.01$.

Interpretation: In order to capture alpha (the abnormal return), inclusion of higher order terms of the normalized characteristics in the CCAR regression considerably inflate the standard errors of alpha, thereby rendering even economically meaningful alphas statistically insignificant.

	IPO			DIV		
	Linear	2nd order	3rd order	Linear	2nd order	3rd order
$\Delta\texttt{beta}$	-0.302	-0.292	0.017	-0.332	-0.245	0.574
	(-0.97)	(-1.00)	(0.05)	(-1.32)	(-0.97)	(1.21)
$(\Delta\texttt{beta})^2$		0.136	0.180		0.607	0.562
		(0.46)	(0.61)		(1.59)	(1.47)
$(\Delta\texttt{beta})^3$			-0.518			-1.459^a
			(-0.91)			(-1.92)
$\Delta\texttt{size}$	-0.101	-0.079	-0.026	0.129	0.138	-0.189
	(-0.43)	(-0.34)	(-0.06)	(0.59)	(0.63)	(-0.38)
$(\Delta\texttt{size})^2$		-0.123	-0.125		-0.193	-0.255
		(-0.46)	(-0.48)		(-0.47)	(-0.61)
$(\Delta\texttt{size})^3$			-0.116			0.360
			(-0.20)			(0.55)
$\Delta\texttt{BM}$	0.701^c	0.678^c	1.136^c	0.302	0.314	0.630
	(3.48)	(3.35)	(3.53)	(1.29)	(1.35)	(1.29)
$(\Delta\texttt{BM})^2$		-0.388	-0.469^a		-0.493	-0.443
		(-1.48)	(-1.74)		(-1.14)	(-1.02)
$(\Delta\texttt{BM})^3$			-0.770^a			-0.582
			(-1.69)			(-0.76)
$\Delta\texttt{mom}$	0.979^c	1.003^c	1.422^c	1.291^c	1.294^c	1.012^b
	(2.99)	(2.98)	(3.37)	(5.52)	(5.38)	(2.03)
$(\Delta\texttt{mom})^2$		-0.086	-0.025		-0.609	-0.626
		(-0.23)	(-0.07)		(-1.35)	(-1.35)
$(\Delta\texttt{mom})^3$			-0.733			0.470
			(-1.33)			(0.56)
$\Delta\texttt{illiq}$	0.724^c	0.686^c	0.317	0.518^a	0.461^a	-0.222
	(2.87)	(2.79)	(0.75)	(1.96)	(1.74)	(-0.38)
$(\Delta\texttt{illiq})^2$		0.591^a	0.577^a		1.515^c	1.493^c
		(1.72)	(1.70)		(2.78)	(2.74)
$(\Delta\texttt{illiq})^3$			0.713			1.201
			(1.20)			(1.26)
$\Delta\texttt{isv}$	-1.781^c	-1.770^c	-0.659	-0.850^c	-0.717^b	0.831
	(-5.03)	(-5.10)	(-1.33)	(-2.95)	(-2.50)	(1.64)
$(\Delta\texttt{isv})^2$		0.057	0.287		-0.086	-0.161
		(0.19)	(0.88)		(-0.19)	(-0.35)
$(\Delta\texttt{isv})^3$			-1.946^c			-2.650^c
			(-2.86)			(-3.26)
$\Delta\texttt{inv}$	0.410^b	0.419^b	0.302	0.431^b	0.443^b	0.012
	(2.03)	(2.08)	(0.93)	(1.97)	(2.04)	(0.02)
$(\Delta\texttt{inv})^2$		-0.343	-0.347		0.519	0.515
		(-1.15)	(-1.16)		(1.30)	(1.28)
$(\Delta\texttt{inv})^3$			0.156			0.642
			(0.32)			(0.83)
$\hat{\alpha}$	-0.547^c	-0.495^a	-0.590^b	-0.059	-0.439	-0.376
	(-3.71)	(-1.87)	(-2.20)	(-0.45)	(-1.23)	(-1.04)
Std. error ($\hat{\alpha}$)	[0.147]	[0.265]	[0.268]	[0.132]	[0.357]	[0.362]
Adjusted R^2	0.003	0.003	0.003	0.003	0.004	0.004
F for linear terms	8.02	7.73	3.72	6.96	6.33	1.63
p-value	0.000	0.000	0.001	0.000	0.000	0.126
F for 2nd order terms		0.99	1.27		3.17	3.14
p-value		0.437	0.262		0.003	0.003
F for 3rd order terms			2.23			2.61
p-value			0.032			0.012
		Samples			Samples	
		Regression	Full		Regression	Full
Mean(CCAR)		-0.936^c	-1.384^c		0.111	0.174^a
T-value		-4.27	-5.33		0.88	1.65
Std. Error (mean)		0.219	0.260		0.126	0.105
BHAR		-7.092^b	-28.374^c		7.015	12.629
t-bhar		-1.97	-6.50		0.75	1.36
N clusters		342	371		370	372
N months		108,005	316,148		25,085	38,001
N firms		3,877	7,347		620	873

Table 3: Normalized firm characteristics and long-run abnormal returns for IPOs and DIVs.

Description: The table presents OLS regressions of monthly continuously compounded abnormal returns (CCARs) for IPOs and dividend initiations (DIVs) based on normalized differences of firm and market characteristics specified by Bessembinder and Zhang (2013). The length of the event period for each stock is up to 60 months or the time of delisting, whichever comes first. The T-ratios of the regression coefficients are in parentheses, and standard errors of alphas are in brackets. The middle portion of the table reports F-statistics and their p-values separately for the joint significance of the linear, squared, and cubic terms in the regressions. The bottom portion reports mean CCARs and their T-values as well as number of clusters over which the cross-sectional correlation robust standard errors by Cameron et al. (2011) (see also Petersen, 2009) are computed. All the T-values, standard errors of alphas, and F-values in the table are based on these cross-sectional correlation robust standard error computations. The mean CCARs should be interpreted as the average monthly abnormal returns for stocks with event periods up to 60 months rather than 5-year average monthly abnormal returns. It is notable that the number of clusters (N clusters) reported in the bottom portion is the effective number of observations for inferences instead of the considerably higher number of months (N months) or number of firms (N firms) reported in the last two rows at the bottom. Similar to Bessembinder and Zhang (2013), it is notable that the number of firms in the regression samples are considerably smaller than in the full samples due to limited data availability for the explanatory variables. Superscripts represent significance levels for two-tailed T-tests as follows: $a = 0.10$, $b = 0.05$, and $c = 0.01$.

Interpretation: In order to capture alpha (the abnormal return), inclusion of higher order terms of the normalized characteristics in the CCAR regression considerably inflate the standard errors of alpha, thereby rendering even economically meaningful alphas statistically insignificant.

	M&A			SEO		
	Linear	2nd order	3rd order	Linear	2nd order	3rd order
$\Delta\mathtt{beta}$	-0.287^a	-0.257	-0.301	-0.262^b	-0.267^b	-0.244
	(-1.72)	(-1.49)	(-1.63)	(-1.97)	(-2.00)	(-1.62)
$(\Delta\mathtt{beta})^2$		-0.014	-0.056^b		-0.023	-0.023
		(-0.84)	(-2.02)		(-1.01)	(-1.04)
$(\Delta\mathtt{beta})^3$			0.004^a			0.000
			(1.87)			(-0.05)
$\Delta\mathtt{size}$	-0.084	-0.068	-0.081	-0.066	-0.070	-0.092
	(-1.31)	(-1.12)	(-1.02)	(-1.22)	(-1.29)	(-1.01)
$(\Delta\mathtt{size})^2$		-0.003^a	-0.004		0.000	0.000
		(-1.68)	(-1.41)		(0.39)	(0.32)
$(\Delta\mathtt{size})^3$			0.000			0.000
			(0.28)			(0.39)
$\Delta\mathtt{BM}$	0.100	0.153	0.132	0.015	-0.010	-0.001
	(0.84)	(0.70)	(0.58)	(0.18)	(-0.12)	(-0.01)
$(\Delta\mathtt{BM})^2$		-0.001	0.001		0.002	0.008
		(-0.34)	(0.06)		(0.84)	(1.21)
$(\Delta\mathtt{BM})^3$			0.000			0.000
			(-0.11)			(-0.78)
$\Delta\mathtt{mom}$	0.436^a	0.410^a	0.485^a	0.382^b	0.557^c	0.618^c
	(1.81)	(1.66)	(1.85)	(2.02)	(2.58)	(2.67)
$(\Delta\mathtt{mom})^2$		0.008	0.028^c		-0.027^b	-0.054
		(0.91)	(2.85)		(-2.30)	(-1.60)
$(\Delta\mathtt{mom})^3$			-0.001^b			0.001
			(-2.51)			(1.18)
$\Delta\mathtt{illiq}$	0.256	0.785^c	0.779^c	0.335^a	0.384	0.489^b
	(1.16)	(2.64)	(2.62)	(1.80)	(1.61)	(1.98)
$(\Delta\mathtt{illiq})^2$		-0.020^b	-0.029		0.003	-0.040
		(-2.26)	(-0.81)		(0.27)	(-1.59)
$(\Delta\mathtt{illiq})^3$			0.000			-0.002^b
			(0.29)			(-2.04)
$\Delta\mathtt{isv}$	-0.956^c	-1.012^c	-1.030^c	-0.966^c	-0.961^c	-1.091^c
	(-3.66)	(-3.64)	(-3.77)	(-4.53)	(-4.59)	(-5.02)
$(\Delta\mathtt{isv})^2$		0.008	-0.014		0.012	-0.012
		(1.28)	(-0.62)		(1.02)	(-1.36)
$(\Delta\mathtt{isv})^3$			0.000			0.001^c
			(1.19)			(4.29)
$\Delta\mathtt{inv}$	0.023	0.039	-0.023	0.097	0.080	0.165^a
	(0.23)	(0.35)	(-0.17)	(1.06)	(0.89)	(1.69)
$(\Delta\mathtt{inv})^2$		-0.002	-0.004		0.001	0.023^b
		(-0.17)	(-0.49)		(0.19)	(2.57)
$(\Delta\mathtt{inv})^3$			0.001			-0.001^b
			(1.15)			(-2.32)
$\hat{\alpha}$	-0.198^b	-0.188^a	-0.132	-0.237^b	-0.237^b	-0.237^b
	(-2.00)	(-1.89)	(-1.40)	(-2.31)	(-2.36)	(-2.34)
Std. error ($\hat{\alpha}$)	[0.099]	[0.099]	[0.094]	[0.102]	[0.101]	[0.101]
Adjusted R^2	0.003	0.003	0.003	0.002	0.002	0.003
F for linear terms	2.88	2.98	3.21	5.01	5.32	5.70
p-value	0.006	0.005	0.003	0.000	0.000	0.000
F for 2nd order terms		1.43	2.16		1.23	2.02
p-value		0.193	0.037		0.285	0.052
F for 3rd order terms			1.73			4.03
p-value			0.101			0.000

	Samples		Samples	
	Regression	Full	Regression	Full
Mean(CCAR)	-0.247^b	-0.091	-0.188^a	-0.215^a
T-value	-2.28	-1.12	-1.77	-1.88
Std. Error (mean)	0.109	0.081	0.106	0.115
BHAR	-0.041	-1.432	-0.811	-4.309
t-bhar	0.00	-0.25	-0.20	-1.23
N clusters	365	371	372	372
N months	99,769	171,935	164,255	221,840
N firms	2,604	4,066	4,205	5,085

Table 4: Non-normalized firm characteristics and long-run abnormal returns for M&As and SEOs.

Description: The table presents OLS regressions of monthly continuously compounded abnormal returns (CCARs) for M&As and SEOs based on differences of firm and market characteristics specified by Bessembinder and Zhang (2013). Unlike Table 2 above as well as Table 4 in Bessembinder and Zhang, original non-normalized values of the factors are used. For comparability purposes, slope coefficients in the table are scaled by standard deviations of the factors. As in Table 2, the length of the event period for each stock is up to 60 months or the time of delisting, whichever comes first. The T-ratios of the regression coefficients are in parentheses, and standard errors of alphas are in brackets. The middle portion of the table reports F-statistics and their p-values for the joint significance of the squared terms in the regressions. The bottom portion reports mean CCARs and their T-values as well as number of clusters over which the cross-sectional correlation robust standard errors by Cameron et al. (2011) (see also Petersen, 2009) are computed. All the T-values, standard errors of alphas, and F-values in the table are based on these cross-sectional correlation robust standard error computations. The mean CCARs should be interpreted as the average monthly abnormal returns for stocks with event periods up to 60 months rather than 5-year average monthly abnormal returns. It is notable that the number of clusters (N clusters) reported in the bottom portion is the effective number of observations for inferences instead of the considerably higher number of months (N months) or number of firms (N firms) reported in the last two rows at the bottom. Similar to Bessembinder and Zhang (2013), it is notable that the number of firms in the regression samples are considerably smaller than in the full samples due to limited data availability for the explanatory variables. Superscripts represent significance levels for two-tailed T-tests as follows: $a = 0.10$, $b = 0.05$, and $c = 0.01$.

Interpretation: Unlike CCAR regressions using normalized firm characteristics in Table 2, regressions based on non-normalized original characteristics do not materially affect abnormal returns (alphas), their standard errors, and thereby inferences, whether or not higher order terms are included into the regressions.

	IPO			DIV		
	Linear	2nd order	3rd order	Linear	2nd order	3rd order
Δbeta	−0.340	−0.315	−0.362	−0.224	−0.228	−0.316^a
	(−1.45)	(−1.51)	(−1.58)	(−1.29)	(−1.26)	(−1.79)
(Δbeta)^2		−0.022	−0.021		−0.031	−0.025
		(−0.52)	(−0.50)		(−0.44)	(−0.35)
(Δbeta)^3			0.008			0.012
			(1.11)			(0.81)
Δsize	−0.122	−0.179	−0.466^a	0.005	−0.004	−0.107
	(−1.11)	(−1.03)	(−1.88)	(0.06)	(−0.04)	(−0.58)
(Δsize)^2		0.002	−0.012^a		0.000	0.011
		(0.62)	(−1.94)		(0.06)	(0.72)
(Δsize)^3			0.001^b			0.001
			(2.41)			(0.74)
ΔBM	0.403^c	0.406^c	0.531^c	0.040	0.067	0.355
	(3.14)	(3.19)	(3.98)	(0.19)	(0.36)	(1.35)
(ΔBM)^2		−0.016	−0.016		−0.007	0.002
		(−1.09)	(−1.43)		(−0.40)	(0.11)
(ΔBM)^3			−0.002^c			−0.001
			(−4.94)			(−1.18)
Δmom	0.181	0.435	0.706^b	0.534^c	0.891^c	1.342^c
	(0.85)	(1.58)	(2.16)	(3.42)	(4.23)	(5.67)
(Δmom)^2		−0.032^b	−0.114^c		−0.065^a	−0.295^c
		(−2.53)	(−2.85)		(−1.87)	(−3.72)
(Δmom)^3			0.003^c			0.012^c
			(2.63)			(3.04)
Δilliq	0.135	0.257^a	0.259	0.101	2.989^b	2.734^a
	(1.02)	(1.74)	(1.32)	(0.34)	(2.11)	(1.89)
(Δilliq)^2		0.004	0.003		0.055^b	−0.171
		(1.34)	(0.32)		(2.07)	(−0.26)
(Δilliq)^3			0.000			−0.004
			(−0.12)			(−0.32)
Δisv	−0.902^c	−0.898^c	−0.895^c	−0.616^b	−0.807^c	−0.811^c
	(−3.96)	(−3.77)	(−3.63)	(−2.48)	(−3.51)	(−3.47)
(Δisv)^2		0.016	0.003		−0.050	0.005
		(0.79)	(0.11)		(−1.11)	(0.10)
(Δisv)^3			0.001			0.005^a
			(1.05)			(1.84)
Δinv	0.136	0.254^a	0.266^b	0.240^a	0.217^a	0.186
	(1.22)	(1.93)	(2.05)	(1.93)	(1.75)	(1.11)
(Δinv)^2		−0.016^a	−0.037^b		−0.006	−0.004
		(−1.79)	(−2.19)		(−1.08)	(−0.68)
(Δinv)^3			0.001			0.000
			(1.18)			(0.70)
$\hat{\alpha}$	−0.531^c	−0.526^c	−0.433^c	−0.148	−0.111	−0.108
	(−4.10)	(−3.90)	(−3.40)	(−1.13)	(−0.76)	(−0.73)
Std. error ($\hat{\alpha}$)	[0.129]	[0.135]	[0.127]	[0.131]	[0.146]	[0.147]
Adjusted R^2	0.002	0.002	0.003	0.002	0.003	0.004
F for linear terms	3.80	4.63	5.32	3.77	5.61	7.82
p-value	0.001	0.000	0.000	0.001	0.000	0.000
F for 2nd order terms		2.13	2.25		1.65	2.09
p-value		0.040	0.030		0.120	0.044
F for 3rd order terms			4.89			2.23
p-value			0.000			0.032

	Samples		Samples	
	Regression	Full	Regression	Full
Mean(CCAR)	−0.936^c	−1.384^c	0.111	0.174^a
T-value	−4.27	−5.33	0.88	1.65
Std. Error (mean)	0.219	0.260	0.126	0.105
BHAR	−7.092^b	−28.374^c	7.015	12.629
t-bhar	−1.97	−6.50	0.75	1.36
N clusters	342	371	370	372
N months	108,005	316,148	25,085	38,001
N firms	3,877	7,347	620	873

Table 5: Non-normalized firm characteristics and long-run abnormal returns for IPOs and DIVs.

Description: The table presents OLS regressions of monthly continuously compounded abnormal returns (CCARs) for IPOs and dividend initiations (DIVs) based on differences of firm and market characteristics specified by Bessembinder and Zhang (2013). Unlike Table 3 above as well as Table 4 in Bessembinder and Zhang, original non-normalized values of the factors are used. For comparability purposes, slope coefficients in the table are scaled by standard deviations of the factors. As in Table 3, the length of the event period for each stock is up to 60 months or the time of delisting, whichever comes first. The T-ratios of the regression coefficients are in parentheses, and standard errors of alphas are in brackets. The middle portion of the table reports F-statistics and their p-values for the joint significance of the squared terms in the regressions. The bottom portion reports mean CCARs and their T-values as well as number of clusters over which the cross-sectional correlation robust standard errors by Cameron et al. (2011) (see also Petersen, 2009) are computed. All the T-values, standard errors of alphas, and F-values in the table are based on these cross-sectional correlation robust standard error computations. The mean CCARs should be interpreted as the average monthly abnormal returns for stocks with event periods up to 60 months rather than 5-year average monthly abnormal returns. It is notable that the number of clusters (N clusters) reported in the bottom portion is the effective number of observations for inferences instead of the considerably higher number of months (N months) or number of firms (N firms) reported in the last two rows at the bottom. Similar to Bessembinder and Zhang (2013), it is notable that the number of firms in the regression samples are considerably smaller than in the full samples due to limited data availability for the explanatory variables. Superscripts represent significance levels for two-tailed T-tests as follows: $a = 0.10$, $b = 0.05$, and $c = 0.01$.

Interpretation: Unlike CCAR regressions using normalized firm characteristics in Table 3, regressions based on non-normalized original characteristics do not materially affect abnormal returns (alphas), their standard errors, and thereby inferences, whether or not higher order terms are included into the regressions.

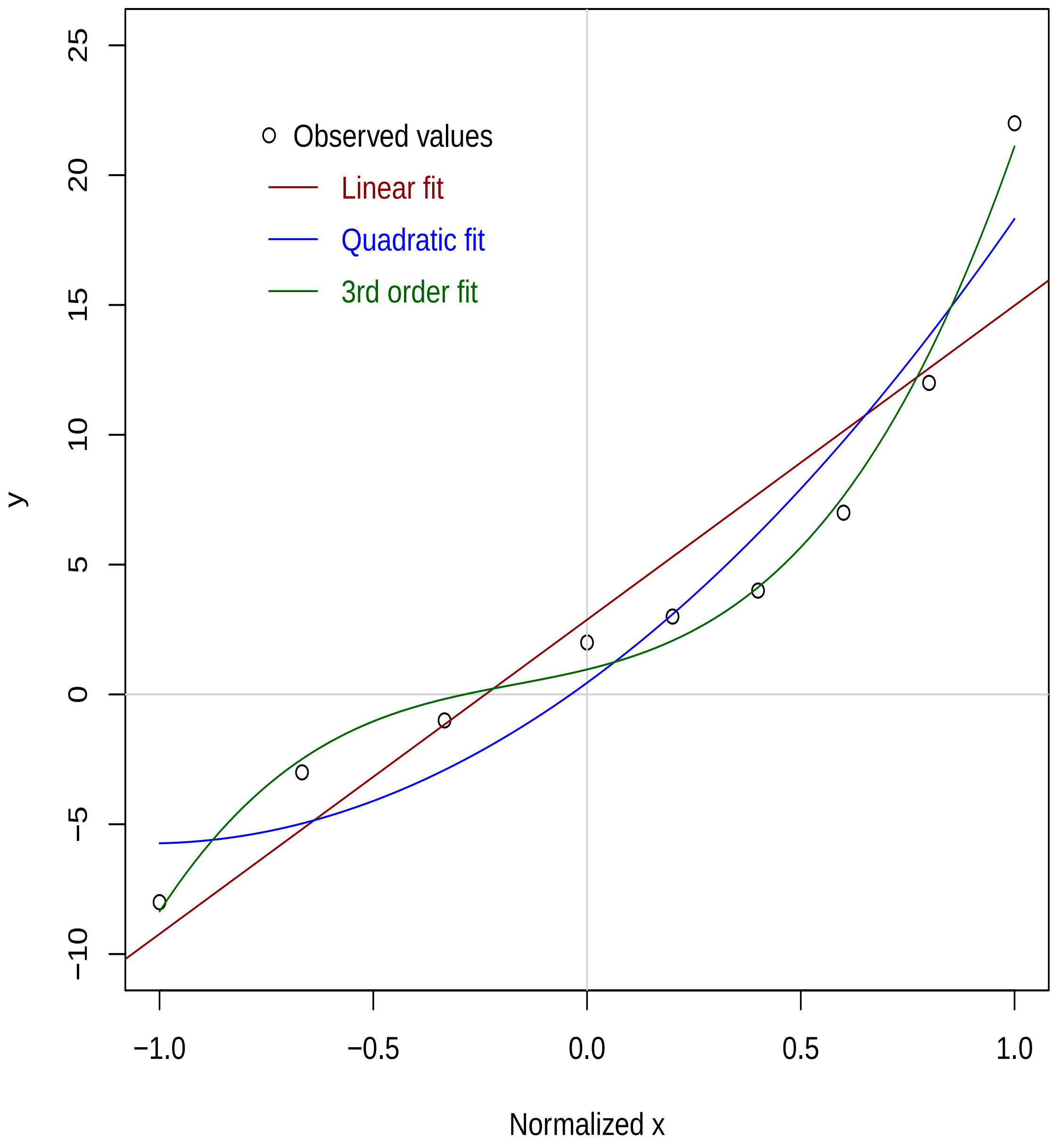

Figure 1: Effect of normalization on regression relationship.

Description: The figure shows that scatter plot of y from the regression relation $y = 2+x$ with $x = (-10, -5, -3, 0, 1, 2, 5, 10, 20)$ based on the Bessembinder and Zhang normalized x-values $(-1, -0.67, -0.33, 0, 0.20, 0.40, 0.60, 0.80, 1)$. Also, the figure shows the linear, quadratic, and third order fitted regression lines.

Interpretation: Normalization non-linearizes the initial relationship $y = 2 + x$. The graph shows that even the third order regression does not capture the implied non-linearity.

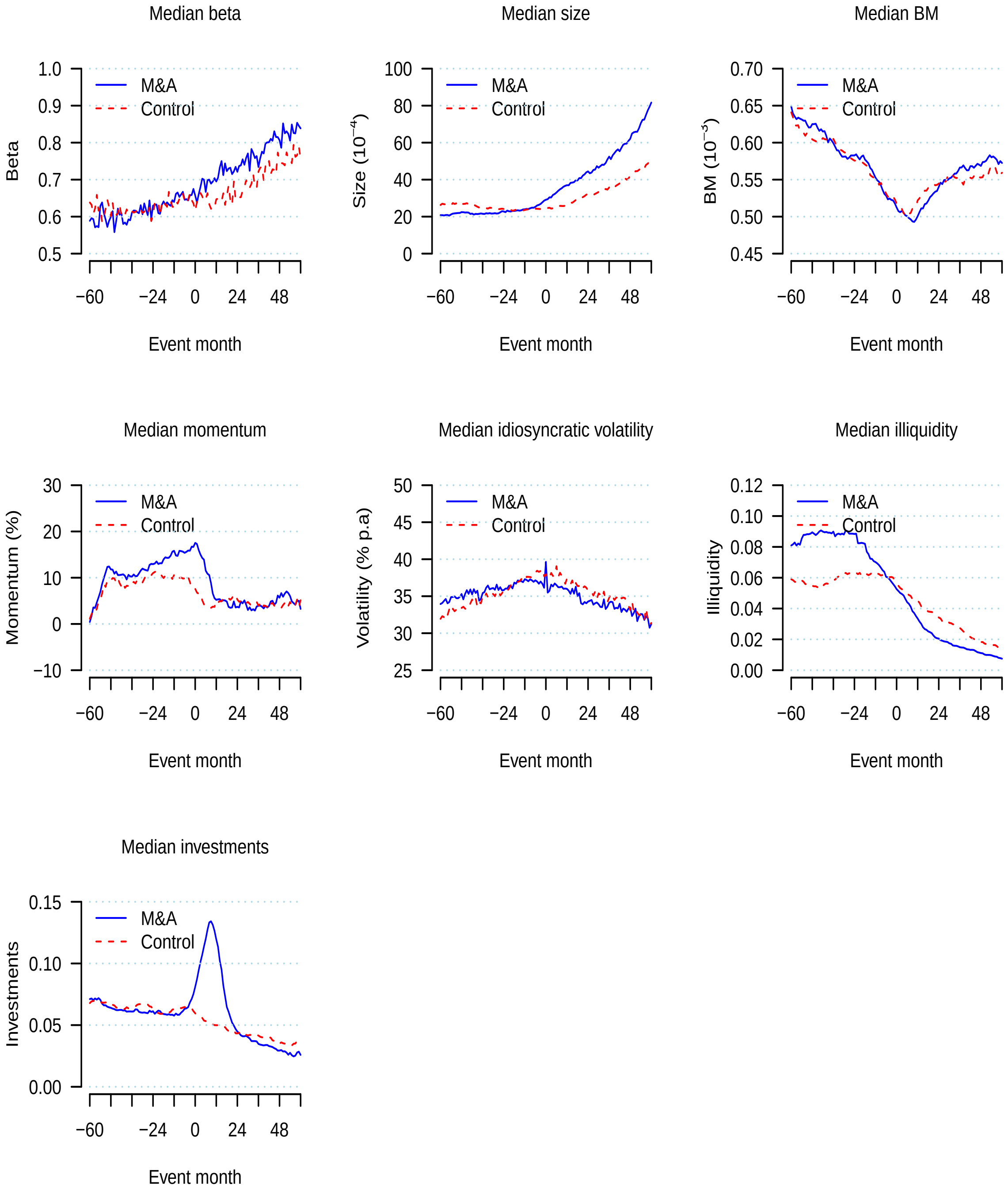

Figure 2: Characteristics of M&A firms and their matched control firms for 60-month event periods before and after the M&A month ($t = 0$).

Description: Following Bessembinder and Zhang, the plots report the median beta, size, BM, momentum, idiosynctratic volatility, illiquidity, and investments. The event sample consists of $n = 4{,}169$ M&As in the CRSP database from January 1980 to December 2005.

Interpretation: The firm characteristics tend to differ on average between event firms and their matches.

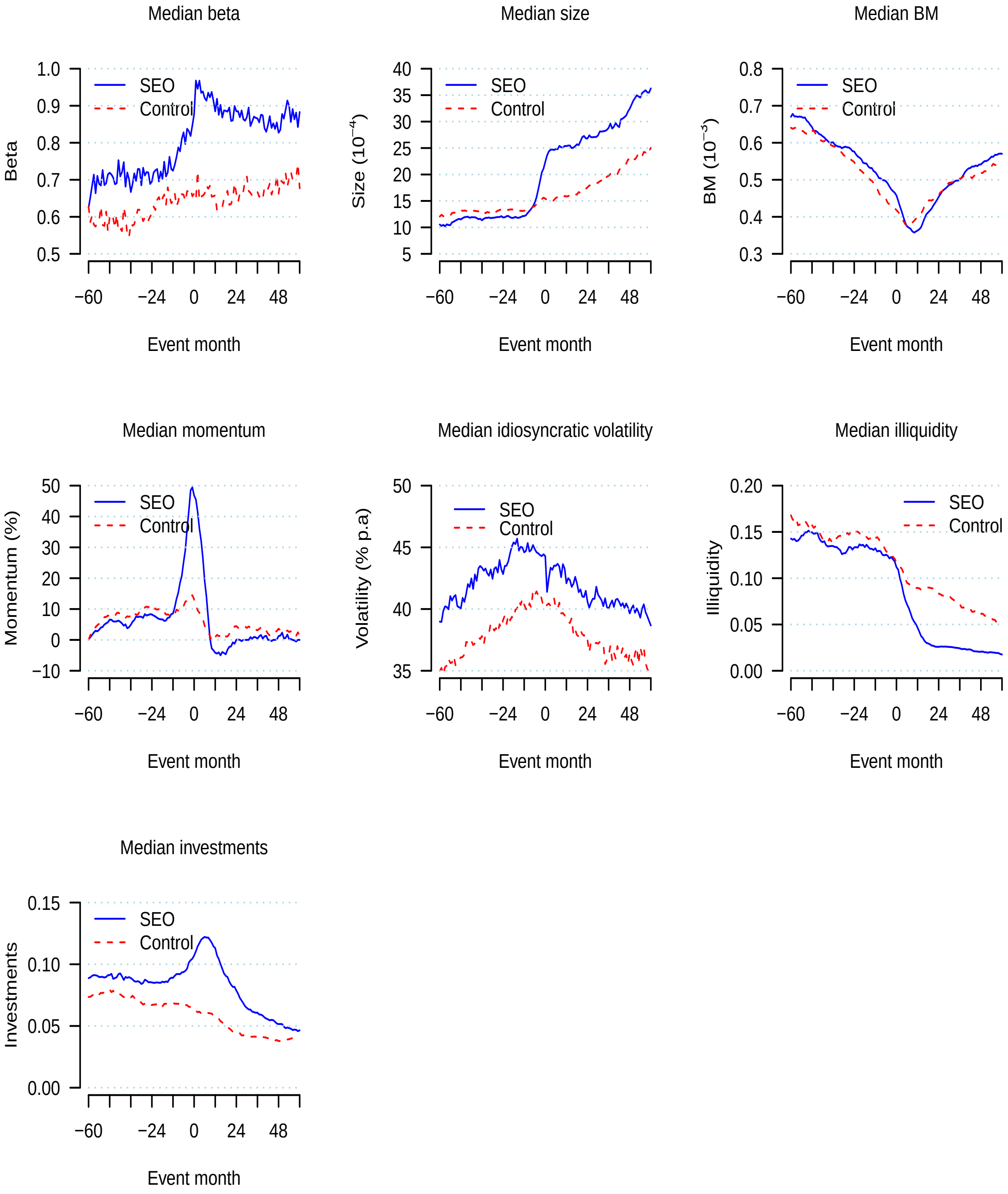

Figure 3: Characteristics of SEO firms and their matched control firms for 60-month event periods before and after the SEO month ($t = 0$).

Description: Following Bessembinder and Zhang, the plots report the median beta, size, BM, momentum, idiosynctratic volatility, illiquidity, and investments. The event sample consists of $n =$ 5,226 SEOs in the CRSP database from from January 1980 to December 2005.

Interpretation: The firm characteristics tend differ on average between event firms and their matches.

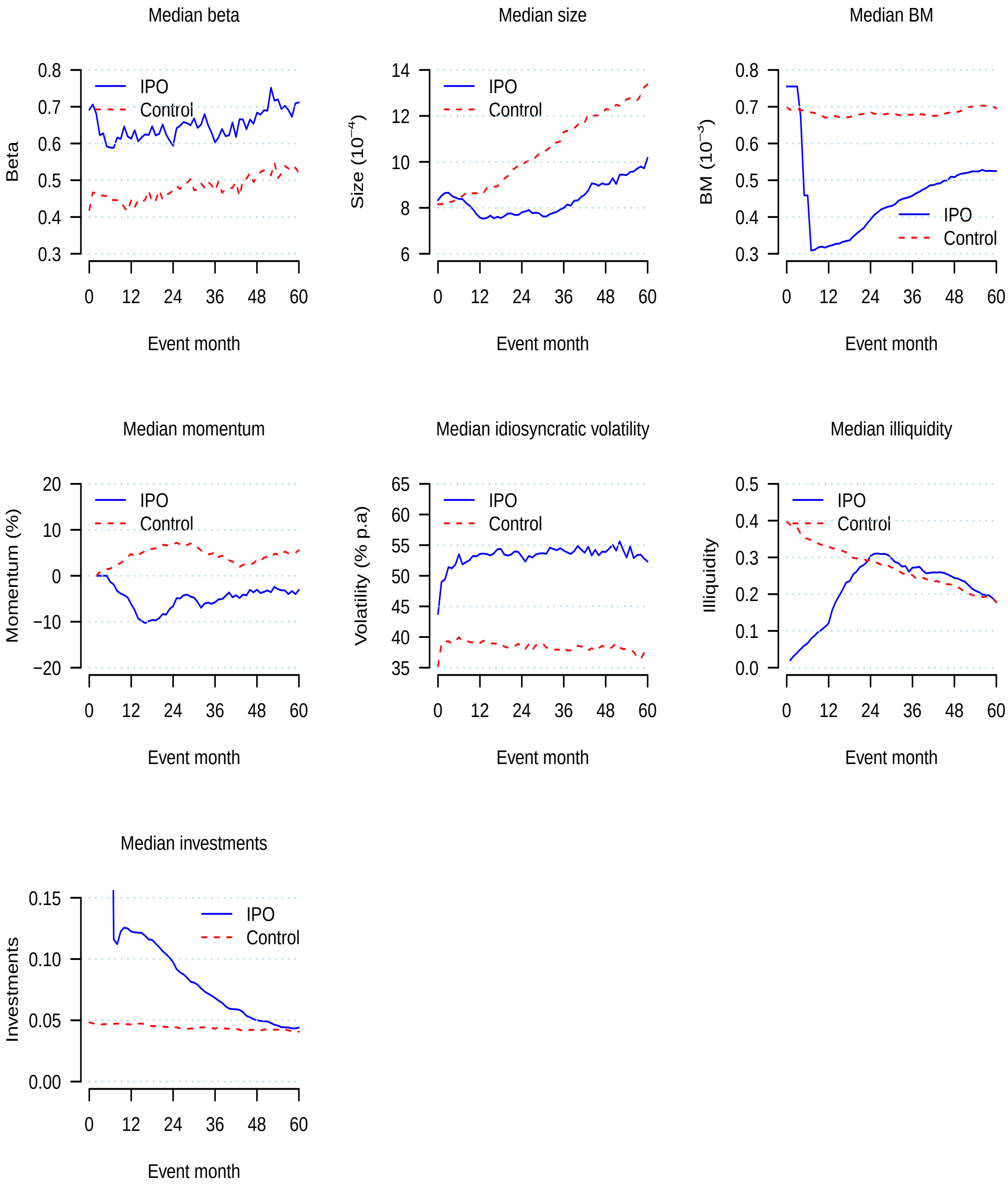

Figure 4: Characteristics of IPO firms and their matched control firms for 60-month event periods after the IPO month ($t = 0$).

Description: Following Bessembinder and Zhang, the plots report average the median beta, size, BM, momentum, idiosynctratic volatility, illiquidity, and investments. The event sample consists of $n = 7{,}347$ IPOs from January 1980 to December 2005.

Interpretation: The firm characteristics tend differ on average between event firms and their matches.

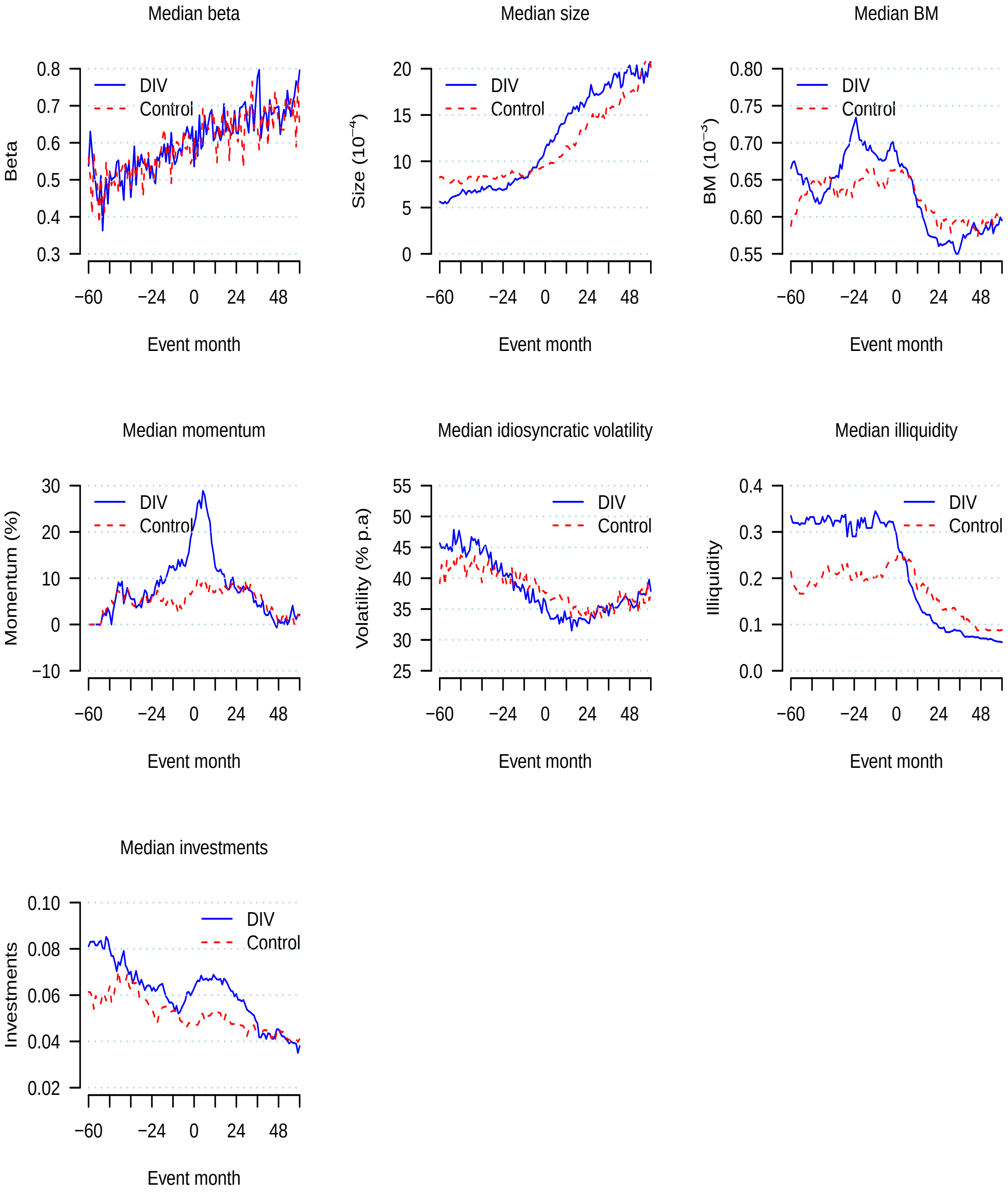

Figure 5: Characteristics of dividend initiation (DIV) firms and their matched control firms for 60-month event periods before and after the DIV month ($t = 0$).
Description: Following Bessembinder and Zhang, the plots report the median beta, size, BM, momentum, idiosynctratic volatility, illiquidity, and investments. The event sample consists of $n = 882$ dividend initiations in the CRSP database from January 1980 to December 2005.
Interpretation: The firm characteristics tend differ on average between event firms and their matches.

A Appendix

A.1 Simulation results

Panel A: Regressor distributions with 0.70 probability of positive values

		Number of clusters								
		20			50			100		
		Number of regressors			Number of regressors			Number of regressors		
Regressor distributions	Alpha	1	3	7	1	3	7	1	3	7
Uniform	alpha(x)	0.999	1.001	1.002	1.001	0.999	1.002	1.000	1.000	1.001
	s.e(alpha)	0.044	0.084	0.151	0.045	0.085	0.151	0.045	0.085	0.152
	alpha(x, x^2)	0.999	1.002	1.001	1.001	0.999	1.000	1.000	1.000	1.003
	s.e(alpha)	0.046	0.092	0.173	0.046	0.093	0.174	0.046	0.093	0.175
	alpha(u)	1.991	3.980	7.949	1.993	3.977	7.950	1.992	3.977	7.946
	s.e(alpha)	0.044	0.078	0.128	0.044	0.079	0.128	0.044	0.079	0.129
	alpha(u, u^2)	1.387	2.170	3.723	1.390	2.167	3.721	1.389	2.167	3.724
	s.e(alpha)	0.048	0.102	0.200	0.049	0.103	0.201	0.049	0.103	0.202
	alpha(u; clust)	2.001	4.008	8.015	2.017	4.048	8.115	2.038	4.114	8.266
	s.e(alpha)	0.048	0.085	0.138	0.048	0.086	0.139	0.048	0.086	0.139
	alpha(u, u^2; clust)	1.392	2.183	3.754	1.400	2.199	3.796	1.408	2.224	3.856
	s.e(alpha)	0.057	0.114	0.216	0.057	0.115	0.218	0.057	0.116	0.220
Triangular	alpha(x)	1.000	1.001	1.003	0.999	1.002	1.002	1.000	0.999	0.999
	s.e(alpha)	0.043	0.080	0.137	0.044	0.081	0.138	0.044	0.081	0.138
	alpha(x, x^2)	1.000	1.000	1.005	0.999	1.003	1.002	1.000	0.998	0.999
	s.e(alpha)	0.045	0.089	0.162	0.046	0.089	0.163	0.046	0.089	0.164
	alpha(u)	1.570	2.711	4.991	1.569	2.711	4.990	1.569	2.708	4.987
	s.e(alpha)	0.043	0.078	0.126	0.044	0.078	0.127	0.044	0.078	0.127
	alpha(u, u^2)	1.090	1.273	1.639	1.090	1.276	1.634	1.090	1.268	1.634
	s.e(alpha)	0.048	0.103	0.203	0.049	0.104	0.205	0.049	0.104	0.206
	alpha(u; clust)	1.579	2.740	5.060	1.593	2.786	5.163	1.617	2.851	5.322
	s.e(alpha)	0.049	0.088	0.140	0.049	0.088	0.141	0.049	0.088	0.142
	alpha(u, u^2; clust)	1.094	1.286	1.668	1.100	1.306	1.703	1.108	1.322	1.759
	s.e(alpha)	0.054	0.112	0.214	0.055	0.113	0.217	0.055	0.113	0.219
Normal	alpha(x)	1.001	1.001	1.001	1.000	1.000	0.996	1.000	0.999	1.002
	s.e(alpha)	0.043	0.080	0.135	0.044	0.080	0.136	0.044	0.081	0.136
	alpha(x, x^2)	1.001	1.000	1.001	1.000	1.000	0.997	1.000	0.999	1.000
	s.e(alpha)	0.045	0.086	0.155	0.045	0.087	0.156	0.045	0.087	0.156
	alpha(u)	1.498	2.492	4.484	1.497	2.492	4.479	1.497	2.492	4.488
	s.e(alpha)	0.044	0.078	0.128	0.044	0.079	0.129	0.044	0.079	0.129
	alpha(u, u^2)	1.067	1.200	1.471	1.067	1.203	1.464	1.067	1.200	1.471
	s.e(alpha)	0.049	0.106	0.210	0.050	0.107	0.212	0.050	0.107	0.212
	alpha(u; clust)	1.508	2.522	4.553	1.522	2.567	4.654	1.546	2.636	4.825
	s.e(alpha)	0.050	0.089	0.144	0.050	0.090	0.144	0.050	0.090	0.144
	alpha(u, u^2; clust)	1.071	1.211	1.497	1.076	1.228	1.525	1.082	1.244	1.575
	s.e(alpha)	0.054	0.113	0.220	0.055	0.114	0.222	0.055	0.115	0.224
Laplace	alpha(x)	1.000	1.000	1.002	1.000	1.001	1.003	0.999	1.000	1.001
	s.e(alpha)	0.043	0.076	0.123	0.043	0.077	0.124	0.043	0.077	0.124
	alpha(x, x^2)	1.000	1.001	1.002	1.000	1.001	1.004	0.999	1.000	1.002
	s.e(alpha)	0.043	0.080	0.136	0.044	0.080	0.137	0.044	0.081	0.137
	alpha(u)	1.060	1.180	1.422	1.059	1.181	1.421	1.059	1.181	1.422
	s.e(alpha)	0.046	0.083	0.136	0.046	0.083	0.137	0.046	0.084	0.138
	alpha(u, u^2)	0.794	0.386	-0.444	0.794	0.383	-0.438	0.792	0.381	-0.438
	s.e(alpha)	0.053	0.116	0.236	0.053	0.117	0.238	0.053	0.117	0.238
	alpha(u; clust)	1.070	1.210	1.492	1.084	1.256	1.596	1.108	1.326	1.760
	s.e(alpha)	0.053	0.095	0.153	0.053	0.095	0.154	0.053	0.095	0.155
	alpha(u, u^2; clust)	0.797	0.394	-0.424	0.800	0.403	-0.392	0.803	0.413	-0.362
	s.e(alpha)	0.055	0.119	0.240	0.055	0.120	0.243	0.055	0.121	0.246
Student $T(5)$	alpha(x)	1.000	1.000	0.998	1.000	0.998	1.000	1.000	0.998	1.004
	s.e(alpha)	0.043	0.078	0.127	0.043	0.078	0.128	0.043	0.078	0.129
	alpha(x, x^2)	1.000	1.000	0.997	1.000	0.998	1.000	1.000	0.998	1.004
	s.e(alpha)	0.043	0.080	0.137	0.044	0.081	0.138	0.044	0.081	0.138
	alpha(u)	1.270	1.813	2.897	1.271	1.811	2.897	1.271	1.810	2.900
	s.e(alpha)	0.046	0.083	0.136	0.046	0.083	0.137	0.046	0.084	0.138
	alpha(u, u^2)	0.950	0.851	0.651	0.951	0.850	0.649	0.951	0.848	0.655
	s.e(alpha)	0.052	0.115	0.232	0.053	0.116	0.234	0.053	0.116	0.235
	alpha(u; clust)	1.280	1.843	2.965	1.296	1.885	3.070	1.318	1.953	3.233
	s.e(alpha)	0.052	0.094	0.152	0.053	0.095	0.153	0.053	0.095	0.153
	alpha(u, u^2; clust)	0.953	0.859	0.670	0.957	0.869	0.694	0.961	0.880	0.727
	s.e(alpha)	0.055	0.119	0.238	0.055	0.120	0.242	0.055	0.121	0.244

Table A.1: Simulation results for alphas and their standard errors in regressions on original and normalized explanatory variables with explanatory variables generated from different distributions.

Panel B: Regressor distributions with 0.60 probability of positive values

		Number of clusters								
		20			50			100		
		Number of regressors			Number of regressors			Number of regressors		
Regressor distributions	Alpha	1	3	7	1	3	7	1	3	7
Uniform	alpha(x)	0.999	1.000	1.001	0.999	1.000	1.000	0.999	1.001	1.000
	s.e(alpha)	0.043	0.076	0.122	0.043	0.076	0.123	0.043	0.077	0.123
	alpha(x, x^2)	0.999	1.001	1.003	0.999	1.000	0.998	0.999	1.001	0.999
	s.e(alpha)	0.047	0.098	0.189	0.048	0.099	0.191	0.048	0.099	0.191
	alpha(u)	1.513	2.543	4.603	1.513	2.544	4.600	1.514	2.545	4.601
	s.e(alpha)	0.042	0.074	0.114	0.043	0.074	0.115	0.043	0.075	0.116
	alpha(u, u^2)	1.194	1.584	2.368	1.193	1.585	2.360	1.194	1.586	2.363
	s.e(alpha)	0.048	0.101	0.199	0.048	0.102	0.200	0.049	0.102	0.201
	alpha(u; clust)	1.517	2.555	4.632	1.523	2.575	4.671	1.534	2.604	4.740
	s.e(alpha)	0.047	0.082	0.127	0.047	0.083	0.128	0.047	0.083	0.128
	alpha(u, u^2; clust)	1.197	1.591	2.384	1.199	1.601	2.400	1.204	1.616	2.433
	s.e(alpha)	0.055	0.111	0.211	0.055	0.112	0.214	0.055	0.113	0.215
Triangular	alpha(x)	1.000	1.001	1.004	0.999	1.000	1.001	0.999	0.999	1.002
	s.e(alpha)	0.042	0.075	0.117	0.043	0.075	0.118	0.043	0.075	0.118
	alpha(x, x^2)	0.999	1.001	1.004	0.999	1.001	1.001	0.999	0.999	1.002
	s.e(alpha)	0.045	0.089	0.165	0.046	0.090	0.166	0.046	0.090	0.167
	alpha(u)	1.254	1.767	2.789	1.254	1.766	2.787	1.255	1.763	2.783
	s.e(alpha)	0.043	0.074	0.115	0.043	0.075	0.116	0.043	0.075	0.116
	alpha(u, u^2)	1.002	1.010	1.020	1.002	1.009	1.021	1.002	1.006	1.018
	s.e(alpha)	0.049	0.103	0.204	0.049	0.104	0.205	0.049	0.104	0.206
	alpha(u; clust)	1.259	1.780	2.819	1.265	1.798	2.863	1.276	1.826	2.931
	s.e(alpha)	0.048	0.085	0.131	0.049	0.085	0.132	0.049	0.085	0.132
	alpha(u, u^2; clust)	1.004	1.016	1.035	1.007	1.024	1.057	1.011	1.032	1.083
	s.e(alpha)	0.053	0.111	0.213	0.054	0.112	0.215	0.054	0.112	0.218
Normal	alpha(x)	1.000	1.000	1.000	1.001	1.000	1.001	1.001	1.001	1.000
	s.e(alpha)	0.042	0.074	0.117	0.043	0.075	0.118	0.043	0.075	0.118
	alpha(x, x^2)	1.000	1.001	1.000	1.001	1.000	1.001	1.001	1.000	0.999
	s.e(alpha)	0.045	0.085	0.152	0.045	0.086	0.153	0.045	0.086	0.154
	alpha(u)	1.245	1.735	2.718	1.247	1.737	2.721	1.246	1.738	2.720
	s.e(alpha)	0.043	0.075	0.116	0.043	0.076	0.118	0.043	0.076	0.118
	alpha(u, u^2)	1.018	1.052	1.121	1.017	1.052	1.122	1.018	1.053	1.123
	s.e(alpha)	0.050	0.106	0.211	0.050	0.107	0.213	0.050	0.107	0.213
	alpha(u; clust)	1.250	1.748	2.748	1.258	1.769	2.797	1.267	1.801	2.867
	s.e(alpha)	0.049	0.086	0.132	0.050	0.086	0.133	0.050	0.086	0.134
	alpha(u, u^2; clust)	1.020	1.058	1.133	1.021	1.064	1.151	1.025	1.075	1.174
	s.e(alpha)	0.054	0.112	0.218	0.054	0.113	0.221	0.054	0.114	0.223
Laplace	alpha(x)	1.000	0.999	0.999	1.000	1.000	1.002	0.999	1.000	1.000
	s.e(alpha)	0.042	0.073	0.113	0.042	0.074	0.114	0.042	0.074	0.114
	alpha(x, x^2)	1.000	1.000	0.998	1.000	1.000	1.002	0.999	1.001	1.000
	s.e(alpha)	0.043	0.078	0.131	0.043	0.079	0.132	0.043	0.079	0.132
	alpha(u)	0.989	0.964	0.916	0.988	0.964	0.919	0.988	0.965	0.918
	s.e(alpha)	0.045	0.079	0.123	0.046	0.080	0.124	0.046	0.080	0.125
	alpha(u, u^2)	0.846	0.540	-0.075	0.847	0.540	-0.068	0.845	0.543	-0.073
	s.e(alpha)	0.053	0.117	0.239	0.053	0.118	0.240	0.053	0.118	0.240
	alpha(u; clust)	0.993	0.977	0.947	0.999	0.997	0.995	1.009	1.028	1.067
	s.e(alpha)	0.052	0.090	0.141	0.052	0.091	0.141	0.052	0.091	0.141
	alpha(u, u^2; clust)	0.848	0.544	-0.066	0.850	0.548	-0.047	0.849	0.557	-0.040
	s.e(alpha)	0.055	0.119	0.242	0.055	0.121	0.244	0.055	0.121	0.247
Student $T(5)$	alpha(x)	1.001	1.000	1.002	0.999	0.999	1.005	1.001	0.999	1.002
	s.e(alpha)	0.042	0.074	0.115	0.042	0.074	0.116	0.042	0.074	0.116
	alpha(x, x^2)	1.001	1.000	1.002	1.000	0.999	1.005	1.001	0.999	1.002
	s.e(alpha)	0.043	0.078	0.129	0.043	0.078	0.129	0.043	0.079	0.130
	alpha(u)	1.132	1.392	1.921	1.131	1.392	1.923	1.132	1.394	1.920
	s.e(alpha)	0.045	0.079	0.123	0.045	0.079	0.123	0.045	0.079	0.124
	alpha(u, u^2)	0.960	0.877	0.718	0.959	0.877	0.720	0.960	0.877	0.713
	s.e(alpha)	0.053	0.116	0.235	0.053	0.116	0.236	0.053	0.117	0.237
	alpha(u; clust)	1.136	1.405	1.951	1.142	1.424	1.998	1.153	1.456	2.065
	s.e(alpha)	0.051	0.089	0.138	0.051	0.090	0.139	0.051	0.090	0.139
	alpha(u, u^2; clust)	0.962	0.881	0.727	0.961	0.885	0.740	0.965	0.893	0.746
	s.e(alpha)	0.055	0.118	0.239	0.055	0.120	0.241	0.055	0.121	0.244

Table A.1 *Continued.*

Description: The table reports average OLS alpha estimates and averages of their clustering robust standard errors from 5,000 simulations of $N = 5{,}000$ observations using various regression specifications. The different average alpha values are estimated as follows: alpha(x) is from the linear model; alpha(x, x^2) is from models with linear and squared x-variables; alpha(u) and alpha(u, u^2) are from linear and quadratic regressions using the Bessembinder and Zhang (2013) normalized x-variables wherein normalization is applied over the whole sample period; and alpha(u; cluster) and alpha(u, u^2; cluster) are from regressions using the Bessembinder and Zhang (2013) normalization cluster wise. Averages of the cross-sectional correlation robust standard errors from the simulations are reported below the alpha estimates. Panels A and B report the results assuming that each of the x-variables in the initial regression has positive values with probabilities 0.70 and 0.60, respectively. The initial regression observations in the simulations are generated from the following model:

$$y = \alpha + \beta_1 x_1 + \ldots + \beta_p x_p + e, \tag{A.1}$$

where p corresponds to either 1, 3, or 7 variables. The explanatory variables are generated in each simulation from the same parent distribution with increasing kurtosis: uniform, triangular, normal, Laplace, and Student-T with 5 degrees of freedom. The respective excess kurtoses (relative to the normal distribution) are $-6/5$ (uniform), $-3/5$ (triangular), 0 (normal), 3 (Laplace), and 6 (Student-T). In each simulation experiment the sets of 1, 3, or 7 explanatory variables are generated independently from the same distribution. The observations are divided into $K = 20$, 50, or 100 equal-sized subgroups, and in each subgroup the intra-class correlation of the error terms is generated by the following random component model:

$$e_{it} = \eta_t + \epsilon_{it} \tag{A.2}$$

where $\eta_t \sim N(0, \sigma_\eta^2)$ and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ are independent and also independent of the x-variables, $i = 1, \ldots, N/K$ ($N = 5000$, $K = 20, 50, 100$). The random component model in equation (A.2) implies error term intra-class correlation of $\rho_e = \sigma_\eta^2/(\sigma_\eta^2 + \sigma_\epsilon^2)$. Because the x-variables are independent, Petersen (2009) shows that the intra-class correlation of the error terms does not affect the OLS standard errors of the slope coefficients. However, the standard errors of the intercept terms are affected. Utilizing equation (4) in Kolari and Pynnönen (2010), we adjust the component variances σ_η^2 and σ_ϵ^2 such that the inflation factor $\sqrt{1 + (n-1)\rho_e}$ equals 2, where $n = N/K$. That is, in the model with only the intercept term, the true standard error of the alpha estimate would be double that of the OLS standard error. The simulations investigate the effect of the normalization on the alpha estimates and their standard errors. All background parameters are the same in each simulation. The standard deviations of the explanatory variables are all equal to 3, the R-square in each original regression is fixed to 0.80, such that with these values the variances of the error terms become $\sigma_e^2 = (1 - R^2)\mathrm{var}[y] = \left(\beta_1^2 \,\mathrm{var}[x_1] + \cdots + \beta_p^2 \,\mathrm{var}[x_p]\right)(1 - R^2)/R^2$. The error component variances are defined so that $\sigma_\eta^2 = \rho_u \sigma_e^2$ and $\sigma_\epsilon^2 = (1 - \rho_e)\sigma_e^2$. The intercept and the slope coefficients in initial regression (A.1) are set equal to unity, i.e., $\alpha = \beta_1 = \cdots = \beta_p = 1$.

Interpretation: Normalizing regressors biases the intercept (alpha), which in financial economics measures abnormal return, for estimates depending on the parent distribution of the regressors and the number of regressors in the model. The normalization inflates standard errors of alphas also. The inflation effect is independent of the distribution of the regressors. Normalized regressors of squared terms are imposed to the regressions. OLS regressions with non-normalized regressors represent unbiased and consistent estimates of the standard errors against which the standard errors of alphas from corresponding regressions with normalized regressors can be compared. With seven regressions, including squared terms in the models with normalized regressors biases the standard errors of alphas (for example) in the case of normal regressors by 44% (Panel A, rightmost column: from 0.156 to 0.244) and in the case of Student-T with 5 degrees of freedom by 77% (Panel A, rightmost column: from 0.138 to 0.244).

A.2 Further IPO results

	IPO on normalized characeristics			IPO on non-normalized characteristisc		
	Linear	2nd order	3rd order	Linear	2nd order	3rd order
$\Delta\texttt{size}$	0.302	0.333^{a}	0.417	-0.035	-0.026	-0.299
	(1.51)	(1.65)	(1.14)	(-0.33)	(-0.17)	(-1.34)
$(\Delta\texttt{size})^2$		-0.125	-0.144		-0.001	-0.014^{b}
		(-0.46)	(-0.53)		(-0.40)	(-2.08)
$(\Delta\texttt{size})^3$			-0.211			0.000^{b}
			(-0.45)			(2.23)
$\Delta\texttt{BM}$	1.113^{c}	1.078^{c}	1.717^{c}	0.567^{c}	0.560^{c}	0.693^{c}
	(4.82)	(4.67)	(4.20)	(4.36)	(4.33)	(5.06)
$(\Delta\texttt{BM})^2$		-0.184	-0.340		-0.015	-0.015
		(-0.79)	(-1.44)		(-0.98)	(-1.24)
$(\Delta\texttt{BM})^3$			-1.115^{b}			-0.003^{c}
			(-2.29)			(-4.94)
$\Delta\texttt{mom}$	1.382^{c}	1.402^{c}	1.552^{c}	0.386	0.795^{c}	1.132^{c}
	(3.90)	(3.86)	(4.33)	(1.50)	(2.66)	(3.17)
$(\Delta\texttt{mom})^2$		-0.135	-0.073		-0.053^{c}	-0.157^{c}
		(-0.36)	(-0.19)		(-3.81)	(-3.29)
$(\Delta\texttt{mom})^3$			-0.293			0.003^{c}
			(-0.56)			(2.82)
$\Delta\texttt{illiq}$	0.772^{c}	0.747^{c}	0.022	0.225^{b}	0.400^{c}	0.424^{c}
	(3.33)	(3.27)	(0.06)	(2.11)	(2.88)	(2.93)
$(\Delta\texttt{illiq})^2$		1.172^{c}	1.130^{c}		0.006^{a}	0.001
		(2.82)	(2.80)		(1.91)	(0.09)
$(\Delta\texttt{illiq})^3$			1.326^{b}			0.000
			(2.39)			(-0.78)
$\Delta\texttt{isv}$	-1.931^{c}	-1.876^{c}	-0.775	-1.224^{c}	-1.185^{c}	-1.172^{c}
	(-4.90)	(-5.19)	(-1.50)	(-4.02)	(-3.98)	(-3.83)
$(\Delta\texttt{isv})^2$		-0.259	-0.015		0.017	0.011
		(-0.88)	(-0.05)		(0.84)	(0.43)
$(\Delta\texttt{isv})^3$			-1.962^{c}			0.001
			(-3.19)			(0.91)
$\Delta\texttt{inv}$	0.115	0.154	-0.127	0.126	0.197	0.192
	(0.56)	(0.77)	(-0.40)	(1.25)	(1.57)	(1.58)
$(\Delta\texttt{inv})^2$		-0.468^{a}	-0.500^{a}		-0.013^{a}	-0.032
		(-1.84)	(-1.92)		(-1.66)	(-1.62)
$(\Delta\texttt{inv})^3$			0.426			0.001
			(0.99)			(1.07)
$\hat{\alpha}$	-0.782^{c}	-0.783^{c}	-0.804^{c}	-0.896^{c}	-0.903^{c}	-0.798^{c}
	(-4.18)	(-3.23)	(-3.43)	(-4.81)	(-4.82)	(-4.59)
Std. error ($\hat{\alpha}$)	[0.187]	[0.243]	[0.235]	[0.186]	[0.187]	[0.174]
Adjusted R^2	0.005	0.005	0.005	0.003	0.004	0.005
F for linear terms	6.92	7.19	6.03	5.35	6.76	7.11
p-value	0.000	0.000	0.000	0.000	0.000	0.000
F for 2nd order terms		2.14	2.59		4.07	2.93
p-value		0.048	0.018		0.001	0.008
F for 3rd order terms			4.23			5.18
p-value			0.000			0.000

	Regression Sample	Full Sample
Mean(CCAR)	-1.321^{c}	-1.384^{c}
T-value	-5.01	-5.33
Std. error (mean)	0.264	0.260
BHAR	-19.646^{c}	-28.374^{c}
t-bhar	-5.487	-6.495
N clusters	354	371
N months	151,944	316,148
N firms	4,616	7,347

Table A.2: Regressions of long-run abnormal returns for IPOs on normalized and non-normalized firm characteristics after removing beta characteristics from the models.

Description: This table replicates Table 3 IPO OLS regressions in the main text with insignificant beta characteristics excluded. Monthly continuously compounded abnormal returns (CCARs) for IPOs are regressed on normalized differences of firm and market characteristics specified by Bessembinder and Zhang (2013). Also, the last three columns of the table give results of regressions on non-normalized characteristics, which replicate IPO regressions in Table 5 without beta characteristics. As the definition of the beta characteristic results in a loss of 18 to 29 months from the beginning of the event period (see footnote 12), most of these months are retained after dropping the insignificant beta characteristics from the regressions. The length of the event period for each stock is up to 60 months or the time of delisting, whichever comes first. The T-ratios of the regression coefficients are in parentheses, and standard errors of alphas are in brackets. The middle portion of the table reports F-statistics and their p-values separately for the joint significance of the linear, squared, and cubic terms in the regressions. The bottom portion reports mean CCARs and their T-values as well as number of clusters over which the cross-sectional correlation robust standard errors by Cameron et al. (2011) (see also Petersen, 2009) are computed. All the T-values, standard errors of alphas, and F-values in the table are based on these cross-sectional correlation robust standard error computations. The mean CCARs should be interpreted as the average monthly abnormal returns for stocks with event periods up to 60 months rather than 5-year average monthly abnormal returns. It is notable that the number of clusters (N clusters) reported in the bottom portion is the effective number of observations for inferences instead of the considerably higher number of months (N months) or number of firms (N firms) reported in the last two rows at the bottom. Similar to Bessembinder and Zhang (2013), it is notable that the number of firms in the regression samples are considerably smaller than in the full samples due to limited data availability for the explanatory variables. Superscripts represent significance levels for two-tailed T-tests as follows: $a = 0.10$, $b = 0.05$, and $c = 0.01$.

Interpretation: Removing insignificant beta characteristics from the IPO regressions in Table 3 of the main text retains the lost 18 to 29 months in the beginning of the event periods of IPOs. These retained months make the weakly statistically significant alphas (abnormal returns) of the regression with squared terms for Bessembinder and Zhang normalized regressors highly economically and statistically significant. Using non-normalized regressors, inclusion of the lost months after dropping the beta characteristics does not affect inferences; in both cases alphas are highly significant.

	IPO on normalized characeristics			IPO on non-normalized characteristisc		
	Linear	2nd order	3rd order	Linear	2nd order	3rd order
$\Delta\texttt{beta}$	-0.476^a	-0.439^a	-0.403	-0.333	-0.348^a	-0.447^b
	(-1.86)	(-1.81)	(-1.22)	(-1.62)	(-1.70)	(-2.07)
$(\Delta\texttt{beta})^2$		-0.348	-0.347		0.011	0.094^a
		(-1.30)	(-1.30)		(0.26)	(1.95)
$(\Delta\texttt{beta})^3$			-0.095			0.011^c
			(-0.20)			(2.96)
$\Delta\texttt{size}$	0.337^a	0.367^a	0.453	-0.035	-0.029	-0.296
	(1.66)	(1.79)	(1.24)	(-0.33)	(-0.18)	(-1.33)
$(\Delta\texttt{size})^2$		-0.088	-0.106		-0.001	-0.014^b
		(-0.33)	(-0.40)		(-0.38)	(-2.06)
$(\Delta\texttt{size})^3$			-0.214			0.000^b
			(-0.45)			(2.22)
$\Delta\texttt{BM}$	1.100^c	1.068^c	1.704^c	0.555^c	0.549^c	0.675^c
	(4.83)	(4.67)	(4.20)	(4.36)	(4.33)	(5.06)
$(\Delta\texttt{BM})^2$		-0.185	-0.341		-0.015	-0.015
		(-0.79)	(-1.45)		(-1.00)	(-1.28)
$(\Delta\texttt{BM})^3$			-1.112^b			-0.003^c
			(-2.29)			(-4.99)
$\Delta\texttt{mom}$	1.409^c	1.418^c	1.527^c	0.401	0.815^c	1.153^c
	(3.91)	(3.85)	(4.30)	(1.54)	(2.69)	(3.18)
$(\Delta\texttt{mom})^2$		-0.090	-0.024		-0.053^c	-0.158^c
		(-0.24)	(-0.07)		(-3.82)	(-3.29)
$(\Delta\texttt{mom})^3$			-0.225			0.003^c
			(-0.43)			(2.82)
$\Delta\texttt{illiq}$	0.717^c	0.695^c	-0.039	0.218^b	0.390^c	0.416^c
	(3.23)	(3.16)	(-0.11)	(2.07)	(2.85)	(2.91)
$(\Delta\texttt{illiq})^2$		1.176^c	1.129^c		0.006^a	0.000
		(2.84)	(2.82)		(1.87)	(0.05)
$(\Delta\texttt{illiq})^3$			1.340^b			0.000
			(2.40)			(-0.82)
$\Delta\texttt{isv}$	-1.840^c	-1.799^c	-0.655	-1.203^c	-1.160^c	-1.150^c
	(-4.98)	(-5.24)	(-1.35)	(-4.04)	(-3.98)	(-3.87)
$(\Delta\texttt{isv})^2$		-0.169	0.088		0.015	-0.010
		(-0.59)	(0.29)		(0.72)	(-0.39)
$(\Delta\texttt{isv})^3$			-2.030^c			0.002
			(-3.36)			(1.54)
$\Delta\texttt{inv}$	0.116	0.156	-0.136	0.132	0.203	0.198^a
	(0.57)	(0.77)	(-0.43)	(1.31)	(1.63)	(1.65)
$(\Delta\texttt{inv})^2$		-0.466^a	-0.500^a		-0.013^a	-0.033
		(-1.83)	(-1.92)		(-1.67)	(-1.63)
$(\Delta\texttt{inv})^3$			0.441			0.001
			(1.03)			(1.07)
$\hat{\alpha}$	-0.775^c	-0.719^c	-0.746^c	-0.888^c	-0.900^c	-0.814^c
	(-4.19)	(-3.06)	(-3.25)	(-4.84)	(-4.84)	(-4.64)
Std. error ($\hat{\alpha}$)	[0.185]	[0.235]	[0.230]	[0.184]	[0.186]	[0.176]
Adjusted R^2	0.005	0.005	0.005	0.003	0.004	0.005
F for linear terms	7.09	7.13	5.18	5.10	6.31	6.58
p-value	0.000	0.000	0.000	0.000	0.000	0.000
F for 2nd order terms		1.94	2.38		3.51	2.62
p-value		0.063	0.022		0.001	0.012
F for 3rd order terms			3.79			4.96
p-value			0.001			0.000

	Regression Sample	Full Sample
Mean(CCAR)	-1.321^c	-1.384^c
T-value	-5.01	-5.33
Std. error (mean)	0.264	0.260
BHAR	-19.646^c	-28.374^c
t-bhar	-5.487	-6.495
N clusters	354	371
N months	151,944	316,148
N firms	4,616	7,347

Table A.3: Regressions of long-run abnormal returns for IPOs on normalized and non-normalized firm characteristics with beta estimated using daily returns in month $t-2$.

Description: This table replicates Table 3 IPO regressions in the main text with the month t beta characteristic estimated similar to indiosyncratic volatility using daily returns in month $t-2$. OLS regressions of monthly continuously compounded abnormal returns (CCARs) for IPOs based on normalized differences of firm and market characteristics specified by Bessembinder and Zhang (2013) are presented in the first three columns, and regressions with non-normalized characteristics are presented in the last three columns. Instead of defining the beta characteristic as in Bessembinder and Zhang, i.e., where beta from July of year t to June of year $t+1$ is estimated from monthly returns from year $t-5$ to year $t-1$ with a minimum of 12 returns, betas used here are estimated from daily returns in month $t-2$. Because IPOs do not have pre-event returns, the Bessembinder and Zhang approach leads to a loss of 18 to 29 months from the beginning of the event period (see footnote 12). Our daily return method of estimating betas leads to a loss of only two months, thus saving a great deal of months in the beginning of the event period. The length of the event period for each stock is up to 60 months or the time of delisting, whichever comes first. The T-ratios of the regression coefficients are in parentheses, and standard errors of alphas are in brackets. The middle portion of the table reports F-statistics and their p-values separately for the joint significance of the linear, squared, and cubic terms in the regressions. The bottom portion reports mean CCARs and their T-values as well as number of clusters over which the cross-sectional correlation robust standard errors by Cameron et al. (2011) (see also Petersen, 2009) are computed. All the T-values, standard errors of alphas, and F-values in the table are based on these cross-sectional correlation robust standard error computations. The mean CCARs should be interpreted as the average monthly abnormal returns for stocks with event periods up to 60 months rather than 5-year average monthly abnormal returns. It is notable that the number of clusters (N clusters) reported in the bottom portion is the effective number of observations for inferences instead of the considerably higher number of months (N months) or number of firms (N firms) reported in the last two rows at the bottom. Similar to Bessembinder and Zhang (2013), it is notable that the number of firms in the regression samples are considerably smaller than in the full samples due to limited data availability for the explanatory variables. Superscripts represent significance levels for two-tailed T-tests as follows: $a = 0.10$, $b = 0.05$, and $c = 0.01$.
Interpretation: Estimating beta characteristics from daily returns allows the usage of the same data as in Table A.2, thereby retaining all but the first two months of the 18 to 29 lost months in IPO regressions in Table 3. Inclusion of beta characteristics in the regression does not alter the high significance of alphas observed in Table A.2 without beta characteristics. These findings further support the conclusion that the weak significance of IPO alpha in the quadratic regression with Bessembinder and Zhang normalized regressors in Table 3 can be attributed to the 18 to 29 lost months at the beginning of each IPO firm's event period.

	IPO on normalized characeristics			IPO on non-normalized characteristisc		
	Linear	2nd order	3rd order	Linear	2nd order	3rd order
$\Delta\texttt{beta}$	−0.405^a	−0.391^a	−0.184	−0.321^a	−0.331^a	−0.387^a
	(−1.78)	(−1.76)	(−0.50)	(−1.67)	(−1.73)	(−1.95)
$(\Delta\texttt{beta})^2$		−0.098	−0.086		−0.013	0.054
		(−0.35)	(−0.30)		(−0.31)	(1.00)
$(\Delta\texttt{beta})^3$			−0.371			0.007^b
			(−0.62)			(2.05)
$\Delta\texttt{size}$	−0.053	−0.035	0.022	−0.096	−0.133	−0.416
	(−0.22)	(−0.15)	(0.05)	(−0.82)	(−0.69)	(−1.61)
$(\Delta\texttt{size})^2$		−0.123	−0.132		0.001	−0.012^a
		(−0.46)	(−0.49)		(0.34)	(−1.89)
$(\Delta\texttt{size})^3$			−0.114			0.000^b
			(−0.19)			(2.35)
$\Delta\texttt{BM}$	0.724^c	0.700^c	1.164^c	0.411^c	0.413^c	0.541^c
	(3.44)	(3.32)	(3.59)	(3.18)	(3.21)	(4.01)
$(\Delta\texttt{BM})^2$		−0.388	−0.471^a		−0.016	−0.017
		(−1.48)	(−1.75)		(−1.09)	(−1.44)
$(\Delta\texttt{BM})^3$			−0.776^a			−0.002^c
			(−1.71)			(−5.02)
$\Delta\texttt{mom}$	0.999^c	1.019^c	1.423^c	0.186	0.449	0.730^b
	(3.02)	(3.00)	(3.37)	(0.87)	(1.62)	(2.20)
$(\Delta\texttt{mom})^2$		−0.069	−0.011		−0.033^b	−0.118^c
		(−0.18)	(−0.03)		(−2.56)	(−2.86)
$(\Delta\texttt{mom})^3$			−0.709			0.003^c
			(−1.29)			(2.64)
$\Delta\texttt{illiq}$	0.724^c	0.681^c	0.313	0.143	0.269^a	0.282
	(2.75)	(2.65)	(0.74)	(1.07)	(1.81)	(1.42)
$(\Delta\texttt{illiq})^2$		0.600^a	0.583^a		0.004	0.002
		(1.72)	(1.70)		(1.38)	(0.24)
$(\Delta\texttt{illiq})^3$			0.710			0.000
			(1.18)			(−0.21)
$\Delta\texttt{isv}$	−1.766^c	−1.756^c	−0.621	−0.938^c	−0.934^c	−0.941^c
	(−4.72)	(−4.84)	(−1.20)	(−3.89)	(−3.73)	(−3.60)
$(\Delta\texttt{isv})^2$		0.092	0.335		0.018	0.000
		(0.30)	(1.00)		(0.92)	(0.01)
$(\Delta\texttt{isv})^3$			−1.993^c			0.001
			(−2.91)			(1.10)
$\Delta\texttt{inv}$	0.423^b	0.433^b	0.298	0.147	0.263^b	0.280^b
	(2.06)	(2.12)	(0.92)	(1.31)	(2.01)	(2.16)
$(\Delta\texttt{inv})^2$		−0.345	−0.352		−0.016^a	−0.037^b
		(−1.16)	(−1.18)		(−1.80)	(−2.16)
$(\Delta\texttt{inv})^3$			0.183			0.001
			(0.38)			(1.13)
$\hat{\alpha}$	−0.573^c	−0.461^a	−0.537^b	−0.615^c	−0.621^c	−0.553^c
	(−3.40)	(−1.71)	(−1.99)	(−3.73)	(−3.68)	(−3.42)
Std. error ($\hat{\alpha}$)	[0.169]	[0.269]	[0.270]	[0.165]	[0.169]	[0.162]
Adjusted R^2	0.003	0.003	0.003	0.002	0.002	0.003
F for linear terms	5.69	5.73	3.63	3.50	4.36	4.78
p-value	0.000	0.000	0.001	0.001	0.000	0.000
F for 2nd order terms		0.99	1.32		2.10	2.25
p-value		0.436	0.239		0.044	0.030
F for 3rd order terms			2.12			4.96
p-value			0.041			0.000

	Regression Sample	Full Sample
Mean(CCAR)	−0.936^c	−1.384^c
T-value	−4.27	−5.33
Std. error (mean)	0.219	0.260
BHAR	−7.092^b	−28.374^c
t-bhar	−1.973	−6.495
N clusters	342	371
N months	108,005	316,148
N firms	3,877	7,347

Table A.4: Regressions of long-run abnormal returns for IPOs on normalized and non-normalized firm characteristics with beta estimated from daily returns and using the event months available in Table 3 for IPOs.

Description: This table replicates Table 3 IPO regressions in the main text with the month t beta characteristic estimated similar to indiosyncratic volatility using daily returns in month $t-2$. Instead of the full data used in Table A.3, the subset available for IPO regressions in Table 3 are used here. Using this subset, the table reports OLS regressions of monthly continuously compounded abnormal returns (CCARs) for IPOs based on normalized differences of firm and market characteristics specified by Bessembinder and Zhang (2013) in the first three columns and regressions with non-normalized characteristics in the last three columns. Instead of defining the beta characteristic as in Bessembinder and Zhang, i.e., where beta from July of year t to June of year $t+1$ is estimated from monthly returns from year $t-5$ to year $t-1$ with a minimum of 12 returns, betas used here are estimated from daily returns in month $t-2$. Because IPOs do not have pre-event returns, the Bessembinder and Zhang approach leads to a loss of 18 to 29 months of returns from the beginning of the event period (see footnote 12). Our daily return method of estimating beta leads to a loss of only two months, thus saving a great deal of months in the beginning of the event period. To assess the effect of dropping the lost months in the Bessembinder and Zhang approach, the table uses only those returns available in their approach. The length of the event period for each stock is up to 60 months or the time of delisting, whichever comes first. The T-ratios of the regression coefficients are in parentheses, and standard errors of alphas are in brackets. The middle portion of the table reports F-statistics and their p-values separately for the joint significance of the linear, squared, and cubic terms in the regressions. The bottom portion reports mean CCARs and their T-values as well as number of clusters over which the cross-sectional correlation robust standard errors by Cameron et al. (2011) (see also Petersen, 2009) are computed. All the T-values, standard errors of alphas, and F-values in the table are based on these cross-sectional correlation robust standard error computations. The mean CCARs should be interpreted as the average monthly abnormal returns for stocks with event periods up to 60 months rather than 5-year average monthly abnormal returns. It is notable that the number of clusters (N clusters) reported in the bottom portion is the effective number of observations for inferences instead of the considerably higher number of months (N months) or number of firms (N firms) reported in the last two rows at the bottom. Similar to Bessembinder and Zhang (2013), it is notable that the number of firms in the regression samples are considerably smaller than in the full samples due to limited data availability for the explanatory variables. Superscripts represent significance levels for two-tailed T-tests as follows: $a = 0.10$, $b = 0.05$, and $c = 0.01$.
Interpretation: Estimating beta characteristics from daily returns as in Table A.3 but using only those months available for IPO regressions in Table 3 allows us to compare whether differences in beta definitions affect alpha inferences in IPO regressions. Regarding alphas, the results in columns 2 to 4 are virtually identical to those for IPO regressions in columns 2 to 4 of Table 3 based on normalized regressors. Also, the alpha results for IPO regressions with non-normalized regressors in columns 5 to 7 of this table are virtually identical to those for IPO regressions based on non-normalized characteristics in columns 2 to 4 in Table 5. Thus, these results, in combination with those of Tables A.2 and A.3, further support the conclusion that the statistically weak significant IPO alpha in the quadratic regression with Bessembinder and Zhang normalized regressors in Table 3 is attributable to the 18 to 29 lost months from the beginning of each IPO firm's event period. Accordingly, because normalization inflates the standard error of alpha and thereby attenuates the power of the related T-test as discussed in Section 1, a reduced number of observations further exacerbates the symptom.