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Unraveling the Impact of Firm Characteristics on Long – Run Abnormal Returns: A Study of U.S. Event Firms

Master Thesis

By

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MSc in Business with Major in Finance

Supervised by

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Abstract

This paper examines the effect of seven firm characteristics on abnormal returns following corporate events, including mergers and acquisitions, and initial and seasoned public equity offerings. Using data from U.S. firms between 1980 and 2017, the buy-and-hold abnormal return (BHAR) approach indicates negative abnormal returns after all three events, while the calendar time portfolio (CTP) method fails to detect abnormal returns following two of the events. Employing a refined BHAR method akin to Bessembinder and Zhang (2013), a simple seven-characteristic regression proves that abnormal returns are fully explained by variations in the characteristics of the event firms. Although this bridges the gap between CTP and BHAR, we show that modifications to both approaches affect inferences made regarding long-run abnormal returns.

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We would like to extend our appreciation to professors Hendrik Bessembinder and Feng Zhang for their groundbreaking work in the field of abnormal returns, specifically their influential study published in 2013. Their research has laid the foundation for our own investigation and has been a valuable reference in shaping our methodology. Our deepest thanks go to our supervisor, Patrick Konermann, whose guidance, expertise, and invaluable feedback have pushed us to think critically and greatly contributed to the quality of this thesis.

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List of Abbreviations

AAR Average Abnormal Return

BHAR Buy-and-Hold Abnormal Return

CAPM Capital Asset Pricing Model

CAR Cumulative Abnormal Return

CRSP The Center for Research in Security Prices

CTP Calendar Time Portfolio

FF3 Fama and French Three-Factor Model

FFC4 Fama and French Three-Factor Model Augmented with Carhart's Momentum Factor

IPO Initial Public Offering

M&A Merger & Acquisition

OLS Ordinary Least Squares

SDC Securities Data Company

SEO Seasoned Equity Offering

WR Wealth Relative

WRDS Wharton Research Data Services

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List of Symbols

$\prod$ Product of a Number of Elements (BHAR Formula)

$\sum$ Sum of a Number of Elements (BHAR Formula)

α Parameter for Intercept

β Parameter for Independent Variables

Δ Parameter for Normalized Differences in Firm Characteristics

1. Introduction and Motivation

The literature has demonstrated that many corporate events, including initial public offerings (IPOs), mergers and acquisitions (M&As), and seasoned equity offerings (SEOs), are followed by apparently abnormal returns – the deviation of a stock's actual return from its expected return. These events are highly relevant due to their frequency and their significant implications for the involved firms and the broader market. However, the accuracy of estimating abnormal returns has been challenged by the 'bad model' problem (Fama, 1998), which arises when traditional models used to estimate expected returns fails to capture the true effect of events on stock prices. As noted by Kothari and Warner (2007), this tends to be the case, particularly for long-run event studies.

Two methods commonly highlight the complexity of the 'bad model' problem in long-term studies. The buy-and-hold abnormal return (BHAR) method compares the buy-and-hold returns of event firms to control firms (benchmark), whereas the calendar time portfolio (CTP) approach examines the average abnormal time series returns of event portfolios. However, these approaches frequently provide contradictory outcomes. For example, Boehme and Sorescu (2002) study 1 645 dividend-initiating firms between 1927–1998 and report a five–year significant BHAR (intercept) of 21.7%, while abnormal returns to calendar time portfolios (alphas) for the same sample are statistically insignificant at 0.21%. Both methods are flawed. BHAR makes the strong assumption that benchmark returns depend *only* on the characteristics used to select control firms. CTP implicitly assumes that event firms' returns are dependent *only* on sensitivities to the factors included in the regressions.

In practice, however, researchers have been able to show that many firm characteristics have significant explanatory power for equity returns, referred to as the 'zoo of factors' by Cochrane (2011). Harvey et al. (2015) examine a collection of 300 papers that investigate the cross-section of expected returns and highlight two important regularities. First, the number of characteristics needed to predict stock returns seem to decrease over time. Second, the authors in this literature illustrate a common procedure, wherein researchers typically analyze their proposed return predictor in isolation, without considering the influence of previously identified predictors. However, there are some exceptions. Adopting Fama-MacBeth (1973) regressions, Haugen and Baker (1996) forecast next month's stock returns relying on 46 factors, while Lewellen (2015) finds only a few significant predictors out of 15 investigated for the cross-section of expected returns. Green et al. (2017) employ Fama-MacBeth regressions in their full sample and find that only 24 out of 94 return predictors offer independent information. Similarly, Freyberger et al. (2017) estimate their model based on 62 characteristics of which only 15 possess incremental explanatory power within their full sample.

We examine whether as little as seven characteristics, drawn from Bessembinder and Zhang (2013), have significant explanatory power for the apparently abnormal returns to event firms: firm size, book-to-market ratio (BM), market beta, idiosyncratic volatility, illiquidity, return momentum, and capital investment. The extant literature has connected each of these seven characteristics to cross-sectional fluctuations in stock returns, thus building the foundation for our following research questions:

- Can differences in firm characteristics between event and control firms fully explain the abnormal returns following corporate events?
- Can modifications to the BHAR and CTP methods help reconcile the contradicting outcomes regarding long-run abnormal returns?

We answer these research questions in three ways. First, in Section 5.1, we replicate the results of Bessembinder and Zhang (2013). Obtaining almost identical results ensures the validity of our model. Second, in Section 5.2, we apply the same methodology to our updated sample. Results found by Bessembinder and Zhang (2013) are persistent, that is, refining the BHAR method to allow for differences in the seven firm characteristics fully explains abnormal returns to firms undergoing any of the three events. The absence of abnormal returns found by CTP in Section 5.3 can, therefore, be largely attributed to imperfect control firm matching.

Third, in Section 5.4, we prove that even minor modifications to the employed approaches can have a profound impact on the conclusions drawn regarding long-term abnormal returns. Hence, the diverging results across the BHAR and CTP methods are not sample-specific per se but rather reflect the implicit assumptions inherent in each method when measuring abnormal returns.

2. Literature Review

The early approach to limiting the 'bad model' problem was to use formal asset pricing models, such as the capital-asset-pricing model (CAPM) to examine long-run abnormal returns (Sharpe, 1964). However, Banz (1981) illustrated that small stocks have higher risk-adjusted returns, on average, than predicted by the CAPM. The importance of this size effect is evidence that the CAPM is misspecified. Based on these findings, Fama and French (1992) show that average stock returns also are related to book-to-market (BM) equity, leading to the introduction of the infamous Fama-French three-factor model (FF3).

Unfortunately, Fama and French (1993) demonstrate that their three-factor model does not fully explain average returns on portfolios formed on size and BM. Testing for long-run abnormal returns using the FF3 model is not optimal, a concern initially raised by Fama (1998). He argues that factor-based approaches may be sufficient in capturing systematic patterns in average returns while acknowledging that the approaches suffer from model misspecification. Extending on this idea, Brav et al. (2000) investigates a sample of IPO and SEO firms from 1975 to 1992. By utilizing time-series factor models, the authors find that the FF3 model captures joint covariation of IPO returns, thus modifying the original FF3 model significantly increases its explanatory power. Also, Loughran and Ritter (2000) find that the FF3 model tends to underestimate abnormal returns when the event being studied is a managerial choice variable, which in our case are IPOs, M&As, and SEOs. As a result, empirically based asset pricing models, such as the FF3 model, lack the ability to test market efficiency. In short, this explains our rationale for controlling for firm characteristics, in addition to size and book-to-market, when implementing the BHAR method, as the literature has pointed out their success in explaining variation in average stock returns.

2.1 Buy-and-Hold Abnormal Returns vs. Calendar Time Portfolio

Beginning with Fama et al. (1969) one can form portfolios of event firms, and average (AAR) or sum (CAR) the average monthly abnormal returns to examine long-term returns. Building on this, Jaffe (1974) and Mandelker (1974) made significant contributions to the financial-economics literature by introducing a calendar time portfolio methodology. Their methodology has garnered support from prominent figures in the field, such as Fama (1998) and Mitchell and Stafford (2000), and has become widely advocated. However, the approach examines the average abnormal time series returns of event portfolios, which may not accurately estimate the return to an investor who holds security for a long post-event period according to Fama (1998) himself.

Among the first to question the usefulness of the CTP approach were Barber and Lyon (1997). They found that the approach yielded misspecified test statistics, because of new listing bias (biased performance following IPOs), rebalancing bias (periodic rebalancing of event portfolios), and positive skewness bias. In a follow-up paper, Lyon et al. (1999) tested for long-run abnormal performance through the BHAR and CTP approach in random samples. They found that both methods yielded well-specified results in random samples, but while the BHAR method was robust also in non-random samples, the CTP method seemed to be faulty. These findings have remained true in recent times, as Asparouhova et al. (2010) have confirmed that the OLS regressions in the CTP approach are subject to rebalancing bias as defined by Barber and Lyon (1997). Loughran and Ritter (2000) also find that the CTP approach has low power to detect abnormal returns, because the method weights each period equally, while corporate events tend to cluster in certain periods.

Following the works of Ikenberry et al. (1995), Barber and Lyon (1997), and Lyon et al. (1999), the characteristic-based matching approach (also known as BHAR) has been widely used as an alternative to the CTP calculation. One appealing aspect of using BHAR is that it better reflects investors' actual investment experience compared to other approaches that involve periodic (monthly) rebalancing when measuring risk-adjusted performance. While BHAR avoids some of the problems mentioned above, Barber and Lyon (1997) report that the skewness bias may be more severe for BHARs and that inferences are less problematic for average monthly returns (AARs or CARs). Fama (1998) documents that the BHAR method does not sufficiently address the issue of cross-sectional correlation of event firm anomalies, and consequently produces misspecified test statistics. Fama also reports that the problem is more severe in long-term BHARs because more firms have events within a five-year window as opposed to a three-day window. Hence, one could argue that the BHAR method should not be used in its traditional form.

Previous research on the implications of using the BHAR and CTP approaches has been mixed. Mitchell and Stafford (2000) and Brav and Gompers (1997) are proponents of the CTP approach and express a preference for using this method. On the other hand, Loughran and Ritter (2000) present an opposing viewpoint, arguing against the utilization of the CTP approach. They suggest that it may introduce biases toward finding results that support the notion of market efficiency, thus vouching for the BHAR approach. Since both the BHAR and CTP are imperfect models, we strive to contribute valuable insights into the long-run return patterns associated with corporate events, by utilizing both approaches and assessing results across methods. When employing the BHAR method, we follow Bessembinder and Zhang (2013). In doing so, we control the relationships between seven firm characteristics and stock returns.

2.2 Firm Characteristics and Abnormal Returns

It is reasonable to ask why it is useful to refine the BHAR approach to control for seven specific firm characteristics when hundreds of factors are available. Although it might seem rather arbitrary, the explanation lies within the existing literature, which has identified five characteristics in particular, excluding size and BM, that are successful in explaining variation in average stock returns. We confirm these findings in Section 4.7.1, proving that there are systematic differences in these characteristics between event firms and control firms. Therefore, as Bessembinder et al. (2019) state: ‘they can potentially explain all the apparently abnormal returns after corporate events’.

The strong negative relation between idiosyncratic volatility and future stock returns was first reported by Ang et al. (2006). The researchers investigate the relationship between volatility and expected returns across different stocks. They find that stocks exhibiting high idiosyncratic volatility tend to have lower average returns. Notably, they observe a substantial and statistically significant disparity of -1.06% per month between the highest and lowest quantile portfolios weighted by value. This study develops a measure for idiosyncratic volatility based on the methodology proposed by Ang et al. (2006). Amihud and Mendelson (1986), were the first to discover a positive relationship between illiquidity and stock returns.

Since then, proxies have yielded mixed results, making the findings difficult to interpret. Brennan and Subrahmanyam (1996) find a negative correlation between illiquidity and expected stock returns, while Amihud (2002) finds a positive relationship. In recent times, Amihud et al. (2015) have extended this research, thereby providing stronger theoretical evidence that the portfolio of the most illiquid stocks generates significantly higher risk-adjusted returns than the portfolio of the most liquid stocks. Prior literature is unclear on the effect of illiquidity on stock returns. Therefore, we indirectly aim to contribute to the discussion of whether increased illiquidity generates higher or lower returns for U.S. event firms by incorporating the illiquidity factor following Amihud (2002).

The literature on momentum profits was first studied by Jegadeesh and Titman (1993), who in general found a positive significant relationship between U.S. stocks and return momentum. The authors discover that executing a strategy that selects stocks based on their six-month historical performance and holds them for another six months results in an average compounded excess return of 12.01% per year. However, Jegadeesh and Titman discover negative return dependence over return horizons longer than one year. As we study long-run abnormal returns over five years, the relation found in this study may contribute to the ongoing discussion and further our understanding of return momentum and its implications for investment decision-making.

Market beta has traditionally been considered a significant determinant of expected stock returns according to the Capital Asset Pricing Model (CAPM). Sharpe (1964) predicts a positive relationship, indicating that a higher beta should offer higher expected returns as compensation for bearing more risk. However, empirical findings on this relationship have been mixed, challenging the straightforward view presented by CAPM. Recent studies have complicated the issue, with researchers reporting a flat or even negative relationship between beta and actual returns, a phenomenon referred to as the 'low-beta anomaly' (Bali et al., 2017). Although the low (high) abnormal returns of stocks with high (low) beta is a persistent anomaly in empirical research, standard asset pricing models maintain a positive relationship between market beta and expected returns.

Loughran and Ritter (1995) find that financing choices associated with increased investment generally result in negative stock returns. On the other hand, Ikenberry et al. (1995) observe that choices associated with decreased investment generally result in positive stock returns. These findings have later been confirmed by Titman et al. (2004), who illustrates that increased capital investments at firms result in negative benchmark-adjusted returns and that increased capital investments lead to lower stock returns for the following five years.

Prior literature has demonstrated the explanatory and predictive capabilities of various characteristics in relation to abnormal returns. Harvey et al. (2015) have extensively identified a substantial number of variables, exceeding 300, that exhibit potential significance in explaining stock returns across different sectors. Recent studies, such as the non-parametric approach by Freyberger et al. (2017), identify 15 independent characteristics that demonstrate explanatory power within their full sample. The success achieved by Kelly et al. (2019) with a latent factor model consists of just eight characteristics. The approach employed in our study, which focuses on a minimal number of the seven characteristics mentioned earlier, contributes to the exploration of the optimal set of characteristics. While the optimal set of characteristics remains a subject of ongoing debate, the consensus favors the utilization of a concise and relevant set of variables for stock return prediction. Table 1 provides a comprehensive summary of key findings in the relevant literature, reinforcing the effectiveness and value of our chosen approach.

Authors	**Firm Characteristic**	**Sample source**	**Sample period**	**Methodology**	**Long-run returns**
Ang et al. (2006)	Idiosyncratic volatility	NYSE stocks (CRSP)	1963-2000	FF3 regressions	-
Amihud et al. (2015)	Illiquidity	US stocks (CRSP), International stocks (Datastream)	1990-2011	Fama-Macbeth regressions	+/-
Jegadesh and Titman (1993)	Momentum	NYSE, Amex and Nasdaq stocks (CRSP)	1965-1989	Buy-sell strategies	-
Bali et al. (2017)	Market beta	NYSE, Amex and Nasdaq stocks (CRSP)	1963-2012	Bivariate and univariate portfolio analysis	-/=
Titman et al. (2004)	Capital investment	NYSE, Amex and Nasdaq stocks (CRSP)	1969-1995	FFC4 regressions	-

Table 1. This table gives an overview of studies that relate to our research. Although the dynamic relationship between firm characteristics and long-run stock returns has been a popular area of research for a long time, it is receiving attention within the financial literature to this day.

2.3 Performance of Event Firms

To illustrate our methodology, we examine three corporate events that have been linked to abnormal stock returns in previous research studies. These events are IPOs, M&As, and SEOs. One notable long-term return anomaly study conducted by Loughran and Ritter (1995) focuses on IPOs and SEOs. Their findings reveal that investing $1 in each IPO or SEO immediately after the event results in approximately 70% of the total wealth generated by applying the same buy-and-hold method to a sample of stocks matched to the IPOs and SEOs. These findings of poor long-term performance for IPOs and SEOs were consistent with earlier empirical results provided by Ibbotson (1975). However, they use matched control firms based only on firm size, as presented by Fama and French (1992), and past stock returns as presented by Jegadeesh and Titman (1993). Since the long-term BHAR in Loughran and Ritter (1995) only controls for a limited number of variables, their results may be influenced by unaccounted factors related to average returns.

In their study, Brav and Gompers (1997) examine this potential scenario by comparing the five-year buy-and-hold returns of IPOs and the returns of portfolios that closely match the IPOs in terms of size and BM ratio. Interestingly, the five-year wealth relative rises from about 0.7 with the Loughran and Ritter size benchmarks to over 1.0, meaning the anomaly disappears.

Moeller et al. (2005) examine 12 023 acquisitions by public firms between 1980-2001 and find no sign of significant long-run abnormal returns around the announcement date for acquiring firms in M&As. However, Asquith (1983) and Agrawal et al. (1992) were among the first to observe that acquiring firms suffered negative abnormal returns for up to five years after merger announcements. Mitchell et al. (2005) use a sample of mergers for 1994-2000 and find negative long-term abnormal returns for acquiring firms.

While we believe our paper will be useful in a wide range of applications, these events offer a valuable illustration of the method due to the significant prior research attention they have received. Table 2 provides an overview of studies that have been conducted regarding long-term abnormal returns to a sampling of corporate events.

Event	Long-term pre-event return	Announcement return	Long-term post-event return
M&As (Asquith, 1983; Agrawal et al., 1992; Loughran and Vijh, 1997; Rau and Vermaelen, 1998; Mitchell et al., 2004; Moeller et al., 2005)	+	0	-
IPOs (Ibbotson, 1975; Loughran and Ritter, 1995; Eckbo et al., 2007)	NA	+	-
SEOs (Loughran and Ritter, 1995; Spiess and Affleck-Graves, 1995; Eckbo et al., 2007)	+	-	-

Table 2. This table gives an overview of previous findings which seek to study long-run stock returns to a sampling of corporate events.

3. Testable Hypothesis and Methodology

This section presents the economic framework for our analysis. We identify the explicit and implicit assumptions made in long-run stock return tests and closely follow Bessembinder and Zhang (2013)[1]. To assess the suitability of the approaches utilized by the authors, we highlight their limitations and modify them accordingly.

3.1 BHAR and Wealth Relative

Extending on Barber and Lyon´s (1997) breakthrough paper on long-run stock performance, we compute the long-run BHAR as

$$\begin{aligned} BHAR_{eT} &= \prod_{t=1}^{T}(1+r_{et}) - \prod_{t=1}^{T}(1+r_{mt}) \\ &= exp\left\{\sum_{t=1}^{T}\ln(1+r_{et})\right\} - exp\left\{\sum_{t=1}^{T}\ln(1+r_{mt})\right\} \qquad (\mathbf{1}) \end{aligned}$$

for event firm *e* over *T* months after a corporate event at date *0*. r_{et} and r_{mt} represent the stock returns of the event firm and its matched control firm, respectively, in month *t*. Furthermore, we follow Loughran and Ritter (1995) in defining wealth relative as

$$WR_{eT} = exp\left\{\sum_{t=1}^{T}[\ln(1+r_{et}) - \ln(1+r_{mt})]\right\}$$

$$= \frac{\prod_{t=1}^{T}(1+r_{et})}{\prod_{t=1}^{T}(1+r_{mt})} \qquad (\mathbf{2})$$

The wealth relative compares the T-period gross return on a \$1 investment in the event firm to the T-period gross return on the same investment in the matching firm. By expressing the estimate of abnormal returns as a function of the implied wealth relative, the issue of compounding in BHARs, highlighted by Fama (1998) and Mitchell and Stafford (2000) is effectively addressed.

[1] Since we are replicating the method used by Bessembinder and Zhang (2013), all formulas in this section is retrieved or inspired by their article. However, we refer to the primary source where this is applicable.

3.1.1 Matching Control Firms

As Eq. (1) highlights, we adopt the approach of Barber and Lyon (1997), who find that the control firm approach effectively addresses the issues mentioned in Section 2.1. By requiring both the event firm and control firm to be listed in the event month, the new listing bias is eliminated. Additionally, calculating returns for both the event and control firms without rebalancing avoids the rebalancing bias. Moreover, the control firm approach ensures that both the event and control firms have an equal likelihood of experiencing large positive returns, thus mitigating the skewness problem. For each event firm, we identify a non-event comparable firm as a common stock that did not engage in the event. Then, we determine whether characteristic-based models can help to fully explain the apparently abnormal returns in the 60 months following corporate events.

For IPOs, the matched firm sample is constructed using a similar approach to Loughran and Ritter (1995). At the end of December following the IPO, each IPO firm is matched with the firm having the closest but greater market capitalization. Furthermore, the matching firm must have been publicly traded for at least five years. This means that the matching firm must not be in our sample of event firms five years before the IPO takes place. For firms undergoing M&As and SEOs, we identify matched firms following Loughran and Ritter (1995), Barber and Lyon (1997), and Eckbo et al. (2000). Each matched firm is selected as having the closest book-to-market ratio across firms with market capitalizations that range between 70% to 130% of the event firm at the end of December preceding the event. To be included, the matching firm must not be in our sample of event firms five years before or after the event date.

Although the abovementioned characteristic-matching procedure has received praise from the extant literature, Section 4.7.1 show that firms matching on firm size and BM do not necessarily match each other in other characteristics. In principle, the issue could be addressed by selecting control firms based on additional firm characteristics. However, the quality of the matches is likely to degrade rapidly as the number of matching characteristics is increased. Therefore, we modify the BHAR method to consist of three main features. First, it maintains the traditional matching procedure as described above. Second, it controls for an array of five firm characteristics, in addition to firm size and BM: market beta, idiosyncratic volatility, return momentum, illiquidity, and capital investment. Third, it allows for variations in these firm characteristics over time.

Following Bessembinder and Zhang (2013), the *market beta*[2] for July of year t to June of year t+1 is estimated using the market model with monthly stock returns during years t-5 to t-1[3]. *Firm size* is measured as market capitalization at the end of the latest June. *BM* for July of year t to June of year t+1 is defined as the book value of common equity at the end of fiscal year t-1, divided by the market value of common equity at the end of fiscal year t-1. We measure *idiosyncratic volatility* following the fundamental paper of Ang et al. (2006). We annualize the standard deviation of the residuals in monthly regressions of daily stock returns during month -2, on the FF3 factors. *Momentum* is computed as the cumulative return from the 12th month to the second month before that month, i.e., over months -12 to -2. As mentioned earlier, *illiquidity* is measured as proposed by Amihud (2002). The illiquidity measure employed for July of year t to June of year t+1 is the daily ratio of absolute stock return to its dollar volume, relative to the market average illiquidity during the same period. *Investment* is measured following Lyandres et al. (2008). Investment for July of year t to June of year t+1 is calculated as the annual change in gross property, plant, and equipment plus inventory, divided by the assets, at the beginning of the fiscal year t.

3.1.2 OLS Regressions

As we have introduced all our explanatory variables, we utilize these to examine the effects of firm characteristics on long-term stock returns following a corporate event. We propose the following regression model, as in Bessembinder and Zhang (2013):

$$\begin{aligned} \ln(1 + r_{et}) - \ln(1 + r_{mt}) = \alpha + \beta_1 \Delta Beta_{et} + \beta_2 \Delta Size_{et} \\ +\beta_3 \Delta BM_{et} + \beta_4 \Delta Momentum_{et} + \beta_5 \Delta Illiquidity_{et} \\ + \beta_6 \Delta IdioVol_{et} + \beta_7 \Delta Investment_{et} \\ + \varepsilon_{et} \qquad \qquad (\mathbf{3}) \end{aligned}$$

[2] Idiosyncratic volatility and market beta are not computed manually. Advancements within WRDS makes us able to directly extract it from this database. The computations of these characteristics in WRDS are consistent with Bessembinder and Zhang (2013), as described above.
[3] Damodaran (2012) suggests computing beta across a five-year period to account for fluctuation in the business cycle and assure enough data points for a meaningful estimation.

$$e = 1, 2, 3, \dots, E; \quad t = 1, 2, 3, \dots, T$$

The BHAR method is refined to focus on differences in monthly log returns[4] and is subject to an extensive cross-section of firm characteristics. We normalize differences in each of the seven firm characteristics across event and control firms. In doing so, we compute the difference in each firm characteristic, between the event firm and control firm, monthly. The positive differences are then sorted from smallest to largest (for $\Delta > 0$), while the negative differences are sorted from least negative to most negative (for $\Delta < 0$). Moreover, the differences are converted to percentile rankings, thereby ranging from -1 to 1.

In numerous empirical studies, the majority of the variation in characteristic values and returns tends to be concentrated in the extremes of the characteristic distribution. There is evidence to suggest that the relationship between characteristics and returns is nonlinear, as highlighted by Fama and French (1995; 2008). Cochrane (2011) speculates on these findings: 'To address these questions in the zoo of new variables, I suspect we will have to use different methods.' We address his suspicion by allowing for possible nonlinear effects by estimating Eq. (3) while including both the level and the square of each normalized difference in firm characteristics. In doing so, we can capture the complex relationship between these variables and stock returns that a linear model may fail to encapsulate. Specifically, we run the following regression:

$$\begin{aligned} \ln(1 + r_{et}) - \ln(1 + r_{mt}) = \alpha &+ \beta_1 \Delta Beta_{et} + \beta_2 \Delta Beta_{et}^2 + \beta_3 \Delta Size_{et} \\ &+ \beta_4 \Delta Size_{et}^2 + \beta_5 \Delta BM_{et} + \beta_6 \Delta BM_{et}^2 + \beta_7 \Delta Momentum_{et} \\ &+ \beta_8 \Delta Momentum_{et}^2 + \beta_9 \Delta Illiquidity_{et} + \beta_{10} \Delta Illiquidity_{et}^2 \\ &+ \beta_{11} \Delta IdioVol_{et} + \beta_{12} \Delta IdioVol_{et}^2 + \beta_{13} \Delta Investment_{et} \\ &+ \beta_{14} \Delta Investment_{et}^2 \\ &+ \varepsilon_{et} \end{aligned} \qquad \mathbf{(4)}$$

The primary focus in Eq. (3) and (4) lies on the intercept variable. The intercept provides an estimation of the mean value of the dependent variable when all independent variables have zero outcomes. Consequently, when estimating Eq. (3)

[4] For the discussion on BHARs vs. log returns, see section 4.7.2.

and (4) without any independent variables, the intercept serves as a measure of the differential in the average compounded return between event and control firms (Bessembinder and Zhang, 2013). When we sequentially add the explanatory variables, the intercept estimates the mean abnormal log return to event firms, conditional on no differences in firm characteristics between event and control firms. By converting the intercept into an equivalent wealth relative ($WR = \exp(\hat{\alpha}T)$), we can estimate the accumulated return to event firms compared to control firms, assuming no disparities in firm characteristics between the two groups. Testing whether

$$\begin{aligned} &H_0: BHAR_{eT} = 0 \\ &H_1: BHAR_{eT} \neq 0 \end{aligned} \qquad \textbf{(5)}$$

Is therefore equivalent to testing whether

$$\begin{aligned} &H_0: WR_{eT} = 1 \\ &H_1: WR_{eT} \neq 1 \end{aligned} \qquad \textbf{(6)}$$

And both are equivalent to testing whether the time series mean log return across the event and control firms is equal.

$$\begin{aligned} &H_0: \alpha = 0 \\ &H_1: \alpha \neq 0 \end{aligned} \qquad \textbf{(7)}$$

Prior literature has firmly stated that firm characteristics are important in influencing long-run abnormal returns. Therefore, before adjusting for differences in firm characteristics, equivalent to running Eq. (3) and (4) without any of the explanatory variables, we expect to see significant abnormal returns, i.e., we would expect to reject the null hypothesis. Failing to reject the null hypothesis in this case would indicate an absence of long-run abnormal returns following the corporate events, which would certainly contradict existing empirical results and findings of recognized researchers as summarized in Table 2. Estimating Eq. (3) and (4) including all explanatory variables will provide an answer to whether we are able to construct a portfolio of firm variables that fully explains abnormal returns to event firms.

3.1.3 Limitations and Further Modifications

In their comprehensive review of many individual financial studies, Fama (1998) and Loughran and Ritter (2000) find that long-run stock returns after corporate events tend to shrink significantly and often disappear when event firms are value-weighted rather than equal-weighted. Therefore, our focus will be on the results obtained when running the pooled regression in Eq. (3) and (4), giving equal weight to each event. This seems the right way to capture long-run abnormal returns, especially since events tend to cluster in time periods as observed by Loughran and Ritter (2000). Petersen (2009), on the other hand, discovers that the residuals in the pooled regression tend to be correlated within firms or across time. This can result in biased estimates of the coefficient standard errors, and thus faulty significance test conclusions. Hence, we cluster the residuals by date for all pooled regressions.

Nevertheless, we perform the value-weighted strategy as a robustness test because the results may be relevant for some stakeholders[5]. Implementing a Fama and Macbeth (1973) regression, we report the estimations results of the same model specification as defined in Eq. (4). In this approach, cross-sectional regression is estimated for every sample month, and finalized estimates are calculated as the time series mean of the monthly estimates[6]. Moreover, an appealing feature of the modified BHAR approach is that it not only allows for variations in firm characteristics beyond size and BM but also allows for changes through time in firm characteristics. To examine the relevance of time variation in firm characteristics versus the introduction of additional characteristics, we estimate Eq. (3) and (4) relying on time-invariant characteristics[7].

3.2 CTP

In addition to the BHAR method, we utilize the CTP approach, to assess whether the results of our refined BHAR method differ from those obtained using the CTP method. The latter approach is formed following Loughran and Ritter (1995), and Brav and Gompers (1997). For each month in our sample period, we form an

[5] We recommend that investors establish their investment strategy before evaluating our outcomes. The regression results of Fama and Macbeth offer valuable insights for stakeholders who intend to maintain a consistent committed capital over time. On the other hand, the pooled OLS regression results are relevant for stakeholders who wish to adjust the committed capital proportionally based on the number of events that take place.

[6] Section 5.4.1

[7] Section 5.4.2

equally weighted portfolio of firms that have undergone relevant corporate events in the last five years[8]. From this, we calculate the excess portfolio return and use this as our dependent variable. The explanatory variables are directly inherited from Fama and French (1993), that is the market, firm size, and BM, augmented with Carhart´s (1997) momentum factor as the independent variables (FFC4). Hence, we run the following regression:

$$\left(R_{pt} - R_{ft}\right) = \alpha + \beta_1 MKT_{et} + \beta_2 SMB_{et} + \beta_3 HML_{et} + \beta_4 UMD_{et} + \varepsilon_{et} \qquad \textbf{(8)}$$

where R_{pt} is the monthly return on the event portfolio, and R_{ft} is the one-month Treasury bill rate. The statistical significance of the intercept indicates whether the long-run performance anomaly to event firms can be resolved by this model. In other words, the hypothesis formed in Eq. (7) applies also to the CTP method. Rejecting the null hypothesis would mean that the calendar time portfolio method indicates an occurrence of abnormal returns for the events. As the existing literature has pointed out disparities between the BHAR method and the CTP method, the expected results from the latter approach seem unclear. We understand that conflicting results may occur, while the opposite is desirable as it would reconcile the two main methods within the area of abnormal stock returns.

3.2.1 Limitations and Further Modifications

In the words of Loughran and Ritter (2000, p. 362): ‘In general, tests that weight firms equally should have more power than tests that weight each time period equally.’ Since the CTP approach weights each period equally, it has a lower power to detect abnormal performance since managers time corporate events to coincide with misevaluations. As a means of addressing the problem, we estimate Eq. (8) following Fama (1998) who suggests weighting the monthly portfolio return by the number of event firms within the given portfolio[9]. Furthermore, we draw inspiration from Jaffe (1974) and Mandelker (1974) who suggest weighting the monthly portfolio return by each month's standard deviation[10], which appears to be the right approach to capture the additional information due to event bunching.

[8] Some sample months contain a small number of event firms. To improve the accuracy of the CTP regression results, we require at least 20 firms in each month for the CTP regressions.

[9] Section 5.4.3

[10] Section 5.4.4

4. Data

This section explains the data utilized in our analysis. No one database contains all the required financial and deal-related data needed for this study. Event firms are retrieved from Securities Data Company (SDC) Platinum while their financial data is retrieved from Wharton Research Data Services (WRDS). Below we describe the main data extraction[11], filtering, and merging process. We have access to the relevant databases through the BI Library.

4.1 IPO Event Firms

IPOs completed by U.S. companies between 1980-2017 are identified using Thomson's Financial SDC database. The sample ends in 2017 for two reasons. First, we are interested in assessing whether Bessembinder and Zhang's (2013) methodology and conclusions remain steadfast for our updated sample. Second, we allow for five years to measure post-event stock returns[12], which is the recommended post-event window in long-run abnormal returns studies according to Fama (1998). It is important to acknowledge that the number of IPOs can vary across studies, in part due to differences in the criteria used to define an IPO. Ritter and Welch (2002) argue that studies of IPOs often exclude closed-end funds and real estate investment trusts (SIC code 6798). American Depositary Receipts are frequently excluded, as they showcase problems with the quality of the data from SDC Platinum. Following Ritter and Welch in filtering the IPO firms, our initial sample of IPOs consists of 10 839 firms.

4.2 M&A Event Firms

M&As completed by U.S. public firms between 1980-2017 are identified using Thomson's Financial SDC database. We impose two filters that follow Betton et al. (2008). First, the acquisition must take one of the following forms: merger (SDC deal form M), acquisition of majority (SDC deal form AM), acquisition of remaining interest (SDC deal form AR), or acquisition of partial interest (SDC deal form AP). Second, the acquisition must be a so-called control bid, which means that the acquirer holds less than 50% of the target and intends to hold more than 50% after the merger. Moreover, we require the transaction value to be more than $5

[11] Appendix A shows the detailed step-by-step data extraction process.
[12] This applies to M&As and SEOs as well.

million to exclude small deals that may have immaterial impacts. Post-filtering, our initial sample of M&As consists of 7016 transactions.

4.3 SEO Event Firms

SEOs completed by U.S. public firms between 1980-2017 are identified using Thomson's Financial SDC database. Consistent with prior research by Eckbo et al. (2007), we exclude American Depository Receipts, Global Depository Receipts, and unit offerings. Financial companies (SIC codes between 6000 and 6999), and public utilities (SIC codes between 4900 and 4999) are excluded from the sample because their capital decisions may be influenced by unique circumstances or specific factors (Flannery and Rangan, 2006). Our initial sample of SEO firms consists of 11 337 observations.

4.4 Financial-Related Data (BHAR)

For every event firm obtained from SDC Platinum, we extract its changeable company identifier (CUSIP) and convert it into a permanent company identifier (PERMNOs) using The Center for Research in Security Prices (CRSP) database[13]. Then, these PERMNOs are utilized within the WRDS database to obtain the event firms' financial data that is needed for our analysis. The databases that have been merged for the modified BHAR approach are reported in Table 3.

File	Database	Frequency	Variable
Security Daily	CRSP/Compustat	Daily	Firm size, Momentum, Illiquidity,
Fundamentals Annual	CRSP/Compustat	Annual	Book-to-market ratio, Investment
Beta Suite	WRDS (Beta)	Daily	Idiosyncratic volatility, Market beta

Table 3. This table provides an overview of all databases used for our modified BHAR analysis. Firm size, return momentum, and illiquidity are all computed from the Daily Security file. Book-to-market ratio and investment are computed from the Fundamentals Annual file, while idiosyncratic volatility and market beta are directly extracted from the Beta Suite database. For the two latter variables, we use an estimation window of 1260 trading days (60 months) and a minimum window of 1 trading day.

As presented in Section 3, we aim to run monthly pooled regressions. Therefore, the frequency of these databases is adapted accordingly. The two daily stock files are converted to monthly values. Regarding the annual stock files, the BM ratio at the end of year T-1 is assigned from July of year T to June of year T+1, while the investment value of year T is assigned from July year T to June year T+1. Hence,

[13] Appendix B explains in detail how we have merged the SDC Platinum and WRDS database.

the frequency of our data is consistent across databases, which is necessary to run the regressions.

4.5 Multifactor Model (CTP)

When utilizing the CTP method, we require a proxy for the risk-free rates. As a proxy for U.S. event firms, we will use the 1-month risk-free rate obtained from the Kenneth R. French Data Library (2021). We utilize monthly frequency not only because this is the approach both Fama and French (1993) and Carhart (1997) suggest, but also because our dataset is based on monthly returns. The remaining factors used in the CTP approach, MKT, SMB, HML, and UMD are retrieved from Kenneth R. French Data Library (2021). For U.S. event firms, we have used the factors for the *U.S. Research Returns Data*.

4.6 Matching Firms and Final Sample

For each event firm, we identify a non-event control firm as a common stock contained in the CRSP database that did not engage in the event. We follow the matching procedure presented in Section 3.1.1. We are able to identify matching firms for 9706 of the IPO firms in our sample, which also is our final IPO sample used in the rest of the paper. For bidding and SEO firms, we are able to identify 2776 and 5018 matching firms, respectively, which also equates to our final sample.

Table 4 reports the number of event firms on an annual basis, indicating that the frequency of events varies significantly over time. The number of IPOs increases substantially in the 1990s to a peak of 735 in 1996 due to the rapid growth of the U.S. economy. The number of M&A deals is severely small before 1984, but substantially increases in the mid-1990s, peaking to 184 in 1997. The number of SEO peaks to 301 in 1983, before declining 81% the following year. Common for all three events is that their number significantly decreases in the early 2000s following the dot com bubble and the associated economic downturn. The number of IPOs and SEOs hit rock bottom in 2008 at 22 and 33, respectively, because of the financial crisis, before increasing by approximately 200% in the following two years. However, the annual number of all three events has had a relatively stable development post the financial crisis.

Year	IPOs	M&As	SEOs
1980	112	2	160
1981	263	25	147
1982	105	39	117
1983	568	31	301
1984	274	51	56
1985	274	68	107
1986	566	79	148
1987	431	80	100
1988	176	74	45
1989	176	66	84
1990	156	56	72
1991	340	43	169
1992	456	50	165
1993	579	71	230
1994	483	112	159
1995	504	134	238
1996	735	162	294
1997	491	184	254
1998	295	181	150
1999	454	179	161
2000	336	170	166
2001	76	124	79
2002	68	70	71
2003	66	60	105
2004	180	74	110
2005	161	58	94
2006	162	59	109
2007	167	81	108
2008	22	44	33
2009	39	30	134
2010	111	42	99
2011	103	27	89
2012	126	28	83
2013	179	43	124
2014	201	38	124
2015	117	59	125
2016	69	41	98
2017	85	41	110
Total	**9706**	**2776**	**5018**

Table 4. This table displays the number of event firms in our final sample, by year.

4.7 Descriptive Data Statistics

In this section, we report summary statistics for our variables and justify the methodology presented in Section 3.

4.7.1 Differences in Firm Characteristics for Event vs. Non-Event Firms

Our objective is to examine the potential of characteristic-based models in explaining the abnormal returns observed in the months following important corporate events. To establish the plausibility of this explanation, it is necessary to demonstrate that firms involved in these events display systematic differences in characteristics that play a crucial role in determining abnormal returns. In Figure 1 – 3 we report the monthly sample medians in the same seven characteristics after the indicated event for IPO, bidding, and SEO firms, as well as their matched control firms.

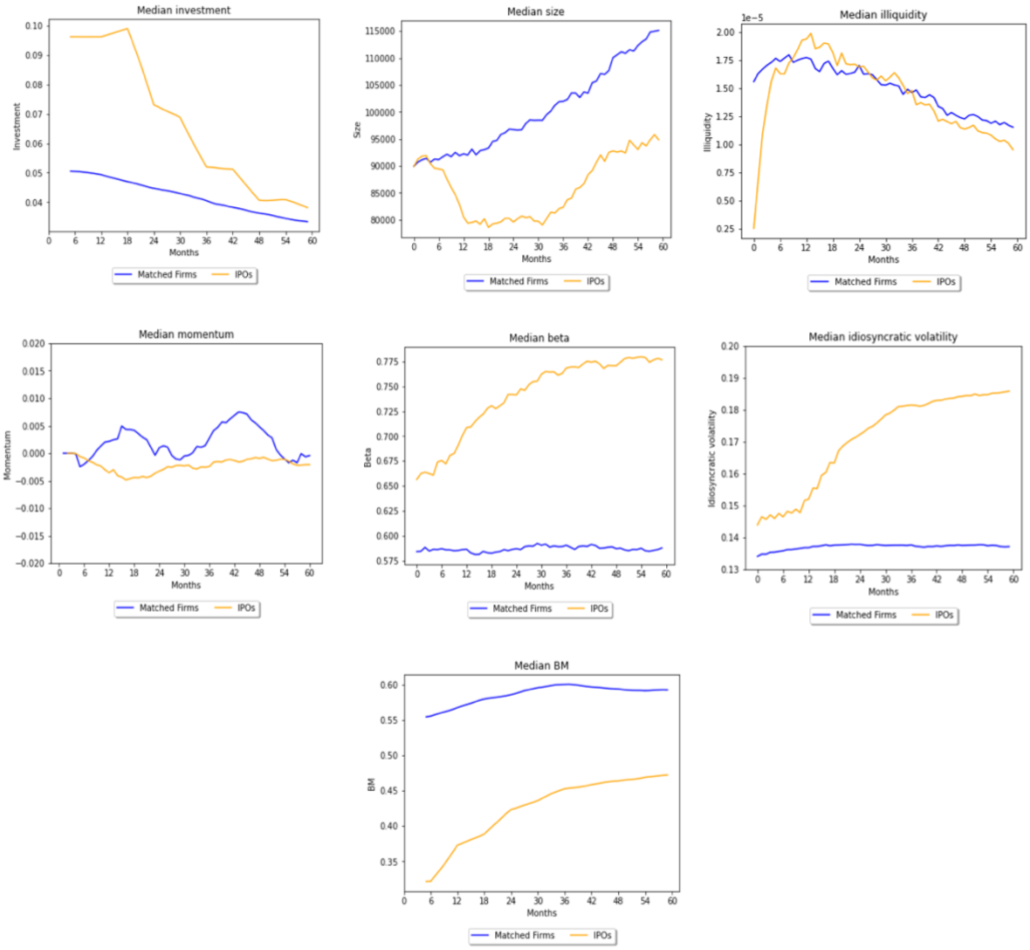

Figure 1. This figure plots the time series of the median beta, size, BM, momentum, idiosyncratic volatility, illiquidity, and investment for sample IPO firms and their size-matched comparable firms, for the 60 months after the initial public offering. Month 0 corresponds to the month of going public. Each IPO firm is matched with a firm with the closest market capitalization at the end of the latest December after the offering (Bessembinder and Zhang, 2013). The sample has 9706 IPO firms over the period 1980–2017.

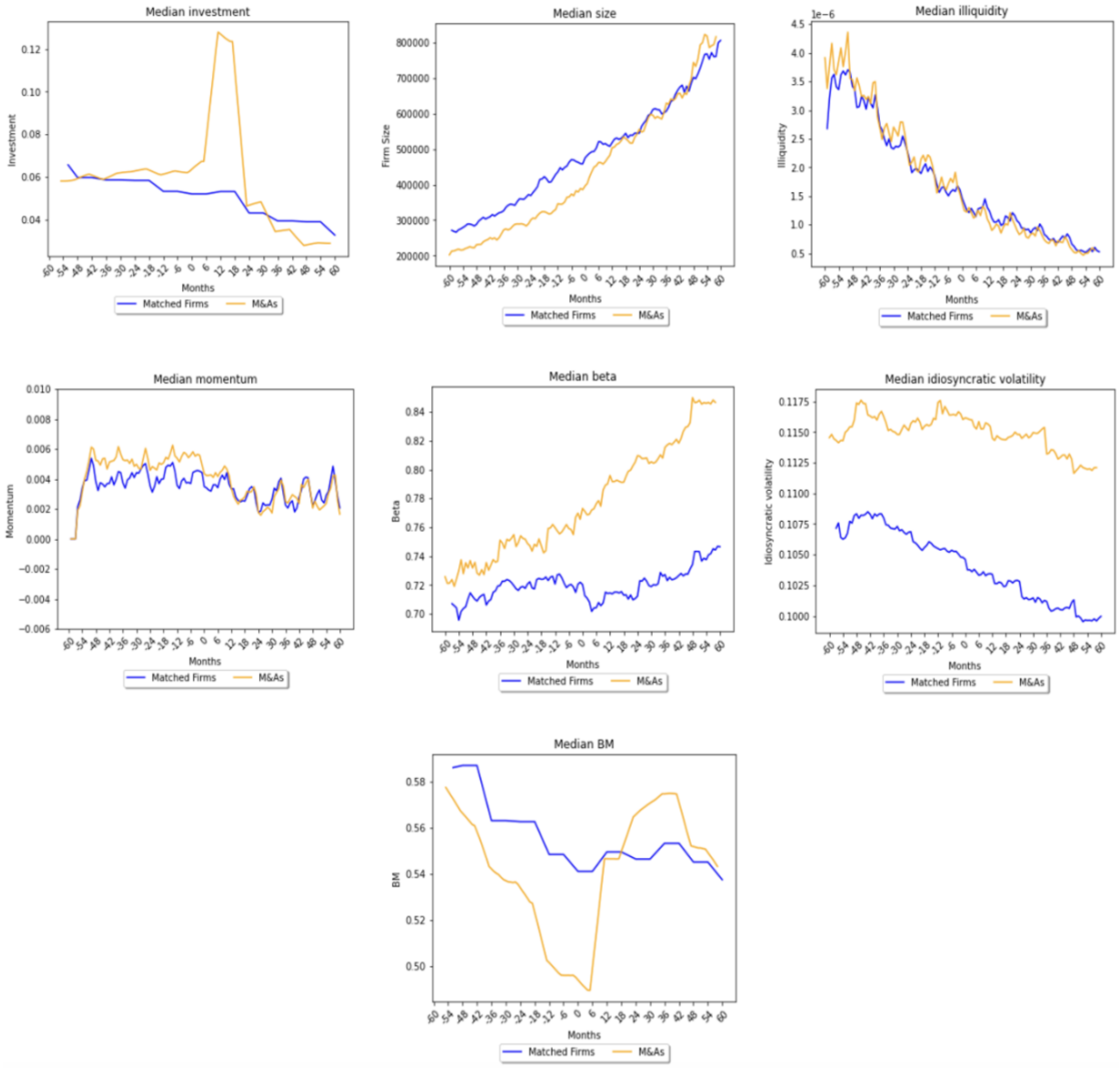

Figure 2. This figure plots the time series of the median beta, size, BM, momentum, idiosyncratic volatility, illiquidity, and investment for sample bidding firms and their size- and BM-matched comparable firms, for the 60 months before and after the merger. Month 0 corresponds to the month of the merger. Each bidding firm is matched with a firm whose size is between 70% and 130% of the bidding firm and has the closest book-to-market ratio at the end of the latest December before the merger (Bessembinder and Zhang, 2013). The sample has 2776 M&A firms over the period 1980–2017.

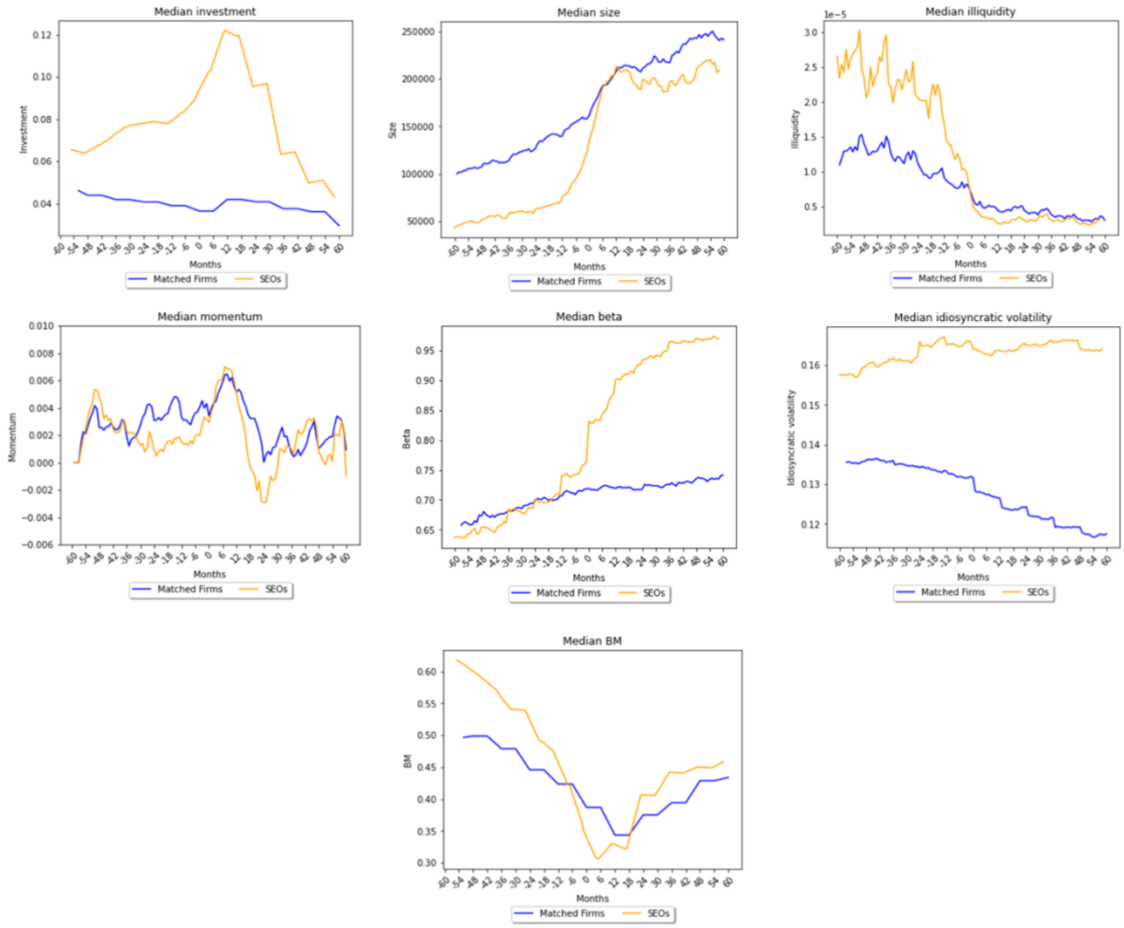

Figure 3. This figure plots the time series of the median beta, size, BM, momentum, idiosyncratic volatility, illiquidity, and investment for sample SEO firms and their size- and BM-matched comparable firms, for the 60 months before and after the equity offering. Month 0 corresponds to the month of the equity offering. Each SEO firm is matched with a firm whose size is between 70% and 130% of the SEO firm and has the closest book-to-market ratio at the end of the latest December before the offering (Bessembinder and Zhang, 2013). The sample has 5018 SEO firms over the period 1980–2017.

Figures 1 – 3 verify that event firms do systematically differ from non-event firms. In particular, firms engaging in IPOs, M&As, and SEOs tend to be smaller than non-event firms. Our findings amplify the results found by Brav et al. (2000), who discovered that firms have low BM ratios during initial public offerings and seasoned equity offerings. IPO firms are much more liquid at the time of going public but maintain moderately better liquidity as compared to their control firms from the 36^{th} month after the IPO. SEO firms are more illiquid 60 months before the issue, while the opposite is true over the 60 months after the issue. These findings are consistent with Butler and Wan (2010) who show that firms that issue securities are more liquid, post-event, than their size and BM-matched control firms. IPO firms and SEO firms have moderately smaller return momentum than their matched firms but invest more over the whole sample period, consistent with the findings of Lyandres et al. (2008). Firms undergoing initial public offerings, mergers, and seasoned equity offerings firms have much higher beta and idiosyncratic volatility than their matched counterparts, especially after the event takes place. Bidding firms have lower BM ratios than their matched firm 60 months before the event, while the opposite is true from the 18th to the 60th month after the merger. Bidding firms always have greater idiosyncratic volatility and market beta than their matched firms over the 120 months around the merger. Lastly, bidding firms have greater return momentum over the 50 months before and 6 months after the event, and greater capital investment than their matched control firms 30 months before and after the merger.

Figures 1 – 3 also present evidence concerning the degree of accuracy over time, regarding the matching between event and control firms in terms of variables used to create the matching sample. Although each sample shows a strong average match at a specific point in time, the level of closeness between the two groups diminishes as time elapses. The median size of bidding firms surpasses that of control firms by the end of the sample period. Furthermore, 18 months after the event, the BM ratio of bidding firms surpasses that of control firms and continues to do so throughout the sample period. The median size of SEO firms increases in the months preceding the offering, equals that of the matched sample in the months after the SEO, but falls short of the matched sample throughout the remaining post-event period. The BM ratio of control firms exceeds that of SEO firms six months before the offering, but not from the 18th month and throughout the sample period. Contrary to bidding and SEO firms, the median size of IPO firms is significantly lower than that of control firms during most of the post-event period, with the largest difference occurring from the 12th to the 30th month after the IPO. These findings reinforce the importance of refining the BHAR method to control for variation over time, even in other characteristics than those used to create the matched firm sample.

4.7.2 BHARs vs. Difference in Log Returns

In Table 5, we additionally report the standardized (scale-invariant) skewness and kurtosis of BHARs and our proposed dependent variable, the difference in monthly log returns. For M&As the kurtosis and skewness do not differ much for BHARs and differences in log returns, such that the results of the regression may not vary substantially depending on what is used as the dependent variable. For IPOs and

SEOs, however, the opposite is true. The skewness of the BHARs is -10.84 (IPOs) and -28.15 (SEOs), while the kurtosis of the BHARs is 165.62 (IPOs) and 819.48 (SEOs). The skewness and kurtosis of log returns differences are considerably lower, with the skewness taking a value of -1.35 (IPOs) and 0.67 (SEOs), and the kurtosis being 14.25 (IPOs) and 1.04 (SEOs). Hence, using differences in monthly log returns as our dependent variable, as opposed to BHARs, yields better statistical properties, and we can alleviate the biases discussed in Section 2.1.

Variable	IPOs		M&As		SEOs	
	60-month BHARs	Difference in log returns	60-month BHARs	Difference in log returns	60-month BHARs	Difference in log returns
Mean	-0.5090	-0.0139	-0.0372	-0.0238	-0.0969	-0.0058
Std. dev.	5.5203	0.2687	2.3534	0.1780	26.6810	-0.1885
Skewness	-10.8369	-1.3497	-1.1709	-0.1212	-28.1460	0.6706
Kurtosis	165.6177	14.2533	13.0556	1.2811	819.4838	1.0388
Minimum	-89.0116	-3.5574	-19.1944	-0.6862	-783.3150	-0.3647
5th percentile	-4.0327	-0.4228	-3.2307	-0.3214	-2.6238	-0.2894
25th percentile	-1.2814	-0.1450	-0.8313	-0.1231	-0.2195	-0.1369
Median	-0.2919	-0.0059	0.0385	-0.0203	0.8568	-0.0200
75th percentile	0.6615	0.1281	0.9026	0.0784	2.5973	0.1022
95th percentile	4.1155	0.3894	2.9190	0.2633	5.2279	0.3322
Maximum	11.6778	2.4350	11.3997	0.8699	5.5970	1.0987

Table 5. This table reports summary statistics of the 60-month BHARs and the difference in monthly log returns between the event firms and their matching firms. BHARs are the differences in the cumulative buy-and-hold returns over the 60-month period between the event firms and their matching firms. The difference in monthly log returns is the difference in monthly log returns between the event firms and their matching firms.

5. Results and Analysis

5.1 Assessing Replicability of Bessembinder and Zhang (2013)

To assess the replicability of Bessembinder and Zhang (2013), we report in Table 6 and Table 7 the regression results for the 1980-2005[14] period obtained through the modified BHAR method and CTP method, respectively. For illustration purposes, we only report the estimated intercept in the regressions, as this is our main variable of interest. Moreover, we only display replication results for one of the events obtained through the modified BHAR method.

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)	OLS (9)	OLS (10)
M&As										
Dependent variable: Difference in log returns										
Constant obtained by Bessembinder and Zhang	-0.0046***	-0.0044***	-0.0050***	-0.0045***	-0.0045***	-0.0041***	-0.0039***	-0.0049***	-0.0035***	0.0002
	(-4.300)	(-4.708)	(-4.364)	(-4.145)	(-4.229)	(-4.175)	(-4.023)	(-3.947)	(-3.492)	(0.105)
Observations	160 900	159 860	160 739	155 132	160 860	160 856	160 845	125 458	120 133	120 133
Constant obtained by us	-0.0043***	-0.0039***	-0.0035***	-0.0037***	-0.0033***	-0.0032***	-0.0032***	-0.0052***	-0.0031***	-0.0027
	(-5.946)	(-5.742)	(-4.659)	(-5.126)	(-4.424)	(-4.159)	(-4.994)	(-5.542)	(-2.981)	(-0.686)
Observations	94 680	93 000	68 056	81 577	67 542	67 002	92 940	61 026	29 820	29 820

Table 6. This table shows the replicating results through the modified BHAR method for the sample of bidding firms by comparing the constant obtained by Bessembinder and Zhang (2013) to the constant obtained by us.

	IPO (1)	M&A (2)	SEO (3)
The calendar time portfolio method			
Dependent variable: Excess portfolio return			
Alpha obtained by Bessembinder and Zhang	0.0020	0.0009	0.0009
	(1.204)	(0.848)	(0.927)
Observations	365	308	369
Alpha obtained by us	0.0017	-0.0002	0.0004
	(1.143)	(-0.200)	(0.386)
Observations	372	370	372

Table 7. This table shows the replicating results through the CTP method for the sample of bidding firms by comparing the Jensen's alpha obtained by Bessembinder and Zhang (2013) to the alpha obtained by us.

First, Table 6 show that the individual slope coefficients associated with the intercept are not identical to Bessembinder and Zhang (2013). The most glaring cause for this is the different number of observations we obtain across Columns 1 – 10, as opposed to the authors. There are several plausible reasons for this, one of which relates to the financial data collection process for event and control firms. Bessembinder and Zhang (2013) do not specify where they extract this data from.

[14] The sample period is constricted to 1980 – 2005 to be consistent with the authors.

Without further context and information, we assume that it is extracted from WRDS as this is the main database designed for quantitative analysis of financial data. However, this is not confirmable and may in practice deviate from the authors. Neither do they specify any data cleaning process, and whether missing or corrupt data have been manually handled. To reduce the impact of data errors in the U.S. data and reduce potential biases arising from low-price, prior studies usually winsorize and quantile stock return data (e.g., Hou et al. 2011; Jensen et al. 2021). In our analysis, we apply a similar approach to our data. Hence, the divergent findings observed in comparison to Bessembinder and Zhang's (2013) results could largely be attributed to differences in handling outliers[15].

Our matching procedure and the computations of dependent and independent variables are directly conditional on the financial data from CRSP. In our case, we suspect that deviations in data cleaning and filtering, inadvertently excluded or altered observations, ultimately resulting in a reduced number of observations. Therefore, since our number of observations deviates from Bessembinder and Zhang (2013), it naturally explains the insubstantially different regression results we obtain.

However, Table 6 showcases two important findings: First, the development of the intercept from Column 1 to Column 9 follows the same direction as Bessembinder and Zhang (2013). Second, the interpretation related to the statistical significance of the intercept across Columns 1 – 10 is completely equal to Bessembinder and Zhang (2013). Table 7 strengthens the replication theory, as we obtain similar Jensen’s alphas as the aforementioned authors. Tables 6 and 7, therefore, showcase that despite the earlier mentioned deviations, our sample is large enough to draw the same conclusions as Bessembinder and Zhang regarding the existence of abnormal returns and the impact of firm characteristics and market factors on these, respectively. We are confident that our methodology is consistent with Bessembinder and Zhang (2013).

[15] In Column 9 we only include event firms that have 60 months of data available for all characteristics. Missing values in firm characteristics explains the significant decrease in data points from Column 1 to Column 9.

5.2 Main Regression Results

This section reports our main results through the estimation of Eq. (3) for the 1980-2017 period. Table 8 relates abnormal returns to IPO firms, Table 9 to bidding firms in M&As, and Table 10 to SEO firms. For Tables 8 to 10 we run pooled OLS regressions when including the standardized difference in each characteristic individually in Eq. (3), as we are interested in examining whether the firm characteristics can individually fully explain any abnormal performance. The most important results are reported when including the standardized differences in each characteristic simultaneously, to understand whether variation in firm characteristics across event and control firms fully explains abnormal returns to event firms. Lastly, we estimate Eq. (4), allowing for non-linear relations between firm characteristics and abnormal returns. This section aims to answer our first research question: *Can differences in firm characteristics between event and control firms fully explain the abnormal returns following corporate events?*

5.2.1 Firm Characteristics and Abnormal Returns After IPOs

Table 8 reports the results of pooled estimation of Eq. (3) and (4) for the IPO sample. In Column 1, which is the mean continuously compounded differential in returns for IPO firms versus control firms, we estimate an intercept of -0.0139. This is by construction equivalent to the mean log return reported in Table 5. The intercept is statistically significant at the 1% level with a t-statistic of -4.173, meaning that we reject the null hypothesis formed in Eq. (7). That is, the IPO firms experience negative abnormal returns of 1.39% over the five years after an IPO. This finding is consistent with previous research, such as Loughran and Ritter (1995) and Eckbo et al. (2007). The estimated intercept of -1.39% equates to a wealth relative of 0.435, which implies an accumulated underperformance of 56.5% for the IPO firms in comparison to their matched control firms.

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)	OLS (9)	OLS (10)
IPOs										
Dependent variable: Difference in log returns										
$\Delta Beta$		-0.0076***							-0.0207***	-0.0186***
		(-3.005)							(-5.768)	(-5.500)
$\Delta Beta^2$										-0.0108
										(-1.551)
$\Delta Size$			0.0292***						0.0117***	0.0040
			(13.000)						(2.792)	(0.907)
$\Delta Size^2$										0.0005
										(0.079)
ΔBM				-0.0073***					-0.0141***	-0.0136***
				(-4.167)					(-4.061)	(-3.642)
ΔBM^2										-0.0240***
										(-3.457)
$\Delta Momentum$					0.0363***				0.0252***	0.0273***
					(17.389)				(8.384)	(8.795)
$\Delta Momentum^2$										0.0722***
										(13.337)
$\Delta Illiquidity$						-0.0153***			-0.0074*	-0.0044
						(-7.343)			(-1.932)	(-1.185)
$\Delta Illiquidity^2$										-0.0396***
										(-7.025)
$\Delta Idio. volatility$							-0.0189***		-0.0238***	-0.0224***
							(-5.630)		(-4.504)	(-4.352)
$\Delta Idio. volatility^2$										-0.0415***
										(-4.838)
$\Delta Investment$								0.0090***	-0.0003	-0.0032
								(5.872)	(-0.102)	(-1.034)
$\Delta Investment^2$										-0.0038
										(-0.662)
Constant	-0.0139***	-0.0131***	-0.0139***	-0.0150***	-0.0098***	-0.0133***	-0.0111***	-0.0164***	-0.0072*	0.0084
	(-4.173)	(-4.071)	(-4.155)	(-4.445)	(-2.709)	(-3.695)	(-3.573)	(-4.750)	(-1.641)	(1.374)
Cluster by date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	323 280	320 231	295 925	207 335	80 117	242 939	318 676	174 560	31 108	31 108
Adjusted R^2	0.000	0.000	0.004	0.000	0.006	0.001	0.002	0.000	0.011	0.020
WR	0.435	0.457	0.435	0.407	0.556	0.450	0.514	0.375	0.649	1.660

Table 8. This table presents the pooled OLS regression results for the difference in monthly log return between the IPO firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each IPO firm is matched with the firm having the closest but greater size (market capitalization) at the end of earliest December after the IPO. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

Columns 2 – 8 report the results obtained by sequentially including the differences between IPO firms and control firms in the seven firm characteristics. Size, momentum, and investment are individually positively and significantly associated with abnormal returns to IPO firms. Beta, BM, illiquidity, and idiosyncratic volatility are individually negatively and significantly associated with abnormal returns. Finding a positive significant relationship between stock momentum and stock returns is consistent with Jeegadesh and Titman (1993), and a negative coefficient on beta, illiquidity, and idiosyncratic volatility is consistent with Bali et al. (2017), Brennan and Subrahmanyam (1996), and Ang et al. (2006) respectively. The significance of the individual slope associated with firm size, in a sample created by matching on this characteristic, highlights the importance of allowing for changes over time in matching variables. The significant coefficients associated with momentum, illiquidity, idiosyncratic volatility, investment, BM, and beta verify the importance of allowing for differences in characteristics, beyond those used to create the matching sample.

Column 9 displays the findings when each of the seven firm characteristics is included in the regression simultaneously. Disparities in size and momentum between IPO and control firms are positively associated with abnormal returns, whereas differences in beta, BM, illiquidity, and idiosyncratic volatility are negatively associated with abnormal returns. Notably, six characteristics are statistically significant in Column 9, reinforcing the importance of controlling for variation in these firm characteristics over time. More importantly, the estimated intercept increases to -0.72% and a wealth relative of 0.649. That is, the inclusion of the set of firm characteristics in the linear pooled regression explains about half of the IPO abnormal returns. However, the estimated intercepts in Columns 2 to 9 range from -1.64% (corresponding to a wealth relative of 0.375) to -0.72% (corresponding to a wealth relative of 0.0.649), remaining statistically significant, barely in Colum 9. Therefore, in the linear OLS specification, we always reject the null hypothesis in Eq. (7), indicating that differences in firm characteristics between IPO firms and control firms are not able to, individually nor collectively, fully explain the apparent abnormal returns to IPO firms after going public.

Lastly, we allow for possible nonlinear effects by estimating Eq. (4). The pooled OLS regression results for IPO firms are reported in Column 10 of Table 6. We note that adding the squared terms barely changes the estimated coefficients on each of the level terms. Strikingly, the estimated intercept is both economically (0.84%) and statistically (t-statistic is 1.374) insignificant. Hence, allowing for non-linear relations between IPO firm characteristics and stock returns, we fail to reject the null hypothesis in Eq. (7), concluding that differences in firm characteristics can fully explain the apparent abnormal returns to IPO firms in the 60 months after going public.

5.2.2 Firm Characteristics and Abnormal Returns after M&As

Turning our attention to Table 9, it reports the results of estimating Eq. (3) and (4) for bidding firms in mergers and acquisitions. Column 1 of Table 9 shows the results obtained by pooled OLS estimation without control for firm characteristics.

The estimated intercept of -0.0238 indicates poor long-run returns to bidding firms. The latter interpretation stems from the intercept being negatively statistically significant at the 1% level, with a t-statistic of -7.933, meaning that we reject the null hypothesis in Eq. (7). The point estimate of -2.38% implies a wealth relative of 0.240, meaning that the average accumulated returns to bidding firms are 76% lower in comparison to control firms selected based on size and BM ratio. A finding of long-term underperformance for bidding firms in mergers and acquisitions is consistent with Loughran and Vijh (1997), Rau and Vermaelen (1998), and Betton et al. (2008).

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)	OLS (9)	OLS (10)
M&As										
Dependent variable: Difference in log returns										
ΔBeta		-0.0063**							-0.0048*	-0.0030
		(-2.340)							(-1.732)	(-1.071)
ΔBeta^2										-0.0048
										(-1.019)
ΔSize			0.0036**						-0.0000	-0.0028
			(2.130)						(-0.029)	(-1.073)
ΔSize^2										0.0098***
										(2.585)
ΔBM				-0.0017					-0.0031	-0.0029
				(-1.005)					(-1.478)	(-1.379)
ΔBM^2										0.0040
										(1.072)
ΔMomentum					0.0108***				0.0132***	0.0128***
					(6.546)				(6.741)	(6.643)
ΔMomentum^2										0.0188***
										(4.950)
ΔIlliquidity						-0.0072***			-0.0075***	-0.0061***
						(-4.592)			(-3.137)	(-2.575)
ΔIlliquidity^2										-0.0165***
										(-4.642)
ΔIdio. volatility							-0.0057*		-0.0128***	-0.0116***
							(-1.894)		(-4.436)	(-4.282)
ΔIdio. volatility^2										-0.0285***
										(-5.699)
ΔInvestment								-0.0063***	-0.0145***	-0.0143***
								(-2.845)	(-6.362)	(-6.476)
ΔInvestment^2										-0.0082**
										(-2.314)
Constant	-0.0238***	-0.0236***	-0.0210***	-0.0216***	-0.0212***	-0.0212***	-0.0234***	-0.0206***	-0.0118***	-0.0035
	(-7.933)	(-8.077)	(-7.295)	(-7.079)	(-7.355)	(-7.292)	(-8.090)	(-5.694)	(-3.693)	(-0.836)
Cluster by date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118 380	118 249	84 808	102 168	84 224	83 794	118 189	76 397	37 740	37 740
Adjusted R^2	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.005	0.009
WR	0.240	0.243	0.284	0.273	0.280	0.281	0.246	0.291	0.494	0.812

Table 9. This table presents the pooled OLS regression results for the difference in monthly log return between the bidding firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each bidding firm is matched with a firm whose size (market capitalization) is between 70% and 130% of the bidding firm and has the closest book-to-market ratio at the end of the latest December prior to the merger. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

Columns 2 – 8 exhibits the results of sequentially incorporating variations in seven firm characteristics between bidding firms and their matched equivalents into the pooled estimation of Eq. (3). Size and momentum are individually positively and significantly associated with abnormal returns to bidding firms. Beta, illiquidity, idiosyncratic volatility, and investment are individually negatively and significantly associated with abnormal returns. Finding a negative coefficient on investment for bidding firms is consistent with Titman et al. (2004). However, the estimated intercept changes only moderately, if at all, across Columns 2 – 8, ranging from -2.36% (wealth relative of 0.243) to -2.06% (wealth relative of 0.291). Each of the intercepts remains statistically significant in each Column, suggesting that the firm characteristics considered here individually explain only 13% of bidder abnormal returns, at most.

Column 9 reports results obtained when including all seven firm characteristics simultaneously. Notably, five firm characteristics are statistically significant at either the 1%, 5%, or 10% level. The significant coefficients associated with beta, momentum, illiquidity, idiosyncratic volatility, and investment showcase that variations in these firm characteristics over time are important drivers of abnormal returns for bidding firms and must be controlled for. The estimated intercept increases to -1.18%, with a corresponding wealth relative of 0.494, but remains statistically significant. Therefore, variations in firm characteristics serve to reduce the estimated long-term underperformance of bidding firms by only 50%. The alternative hypothesis in Eq. (7) is not supported in the linear OLS specification.

Column 10 of Table 9 reports the pooled OLS regression results for our sample of bidding firms with both the level and the square of each of the seven characteristics included as explanatory variables. As in the case of IPO firms, adding the squared terms barely changes the estimated coefficients on each of the level terms. However, we notice that the estimated intercept becomes economically (-0.35%) and statistically (t-statistic is -0.836) insignificant in the non-linear specification. Hence, allowing for non-linear relations in our bidding sample, the pooled OLS provides evidence that variation in the firm characteristics can fully explain the abnormal returns to bidding firms in the 60 months after the merger. We fail to reject the null hypothesis in Eq. (7), which is consistent with Moeller et al. (2005), Harford (2005), and Rau & Vermaelen (1998). That is, there is no long-run abnormal return to bidder firms over the 1980 to 2017 period.

5.2.3 Firm Characteristics and Abnormal Returns after SEOs

Table 8 presents the results of estimating Eq. (3) and (4) for firms engaging in SEOs. The estimated intercept of -0.0058 in Column 1 indicates that SEO firms have -0.58% lower mean log returns per month than control firms. Expectedly, the estimated intercept is statistically significant at the 5% level with a t-statistic of -2.328, and we, therefore, reject the null hypothesis in Eq. (7). The discovery of negative abnormal long-run returns for companies in the 60 months following SEOs aligns with the findings of Loughran and Ritter (1995), Spiess and Affleck-Graves (1995), and Eckbo et al. (2007). The intercept of -0.58% is equivalent to a wealth relative of 0.705, indicating an accumulated underperformance of 29.5% for SEO firms when compared to their matched peers.

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)	OLS (9)	OLS (10)
SEOs										
Dependent variable: Difference in log returns										
$\Delta Beta$		-0.0000							-0.0020	-0.0024
		(-0.059)							(-1.013)	(-1.147)
$\Delta Beta^2$										-0.0027
										(-0.708)
$\Delta Size$			-0.0051***						0.0019***	-0.0004
			(-3.263)						(0.902)	(-0.193)
$\Delta Size^2$										-0.0067**
										(-2.119)
ΔBM				-0.0025*					0.0050**	0.0061***
				(-1.677)					(2.369)	(2.899)
ΔBM^2										-0.0071**
										(-2.002)
$\Delta Momentum$					0.0204***				0.0220***	0.0225***
					(14.770)				(11.492)	(11.173)
$\Delta Momentum^2$										0.0261***
										(6.999)
$\Delta Illiquidity$						0.0026*			-0.0017	-0.0023
						(1.717)			(-0.830)	(-1.111)
$\Delta Illiquidity^2$										-0.0097***
										(-2.891)
$\Delta Idio.volatility$							0.0038**		0.0022	0.0034
							(2.117)		(0.955)	(1.480)
$\Delta Idio.volatility^2$										-0.0051
										(-1.410)
$\Delta Investment$								0.0005	-0.0029*	-0.0033*
								(0.484)	(-1.708)	(-1.939)
$\Delta Investment^2$										0.0078**
										(2.417)
Constant	-0.0058**	-0.0058**	-0.0013	-0.0060**	-0.0015	0.0001	-0.0065***	-0.0066***	-0.0029	-0.0038
	(-2.328)	(-2.371)	(-0.506)	(-2.379)	(-0.595)	(0.048)	(-2.681)	(-2.604)	(-1.138)	(-1.027)
Cluster by date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	216 420	212 285	124 232	176 225	119 842	114 575	212 285	163 855	41 820	41 820
Adjusted R^2	-0.000	-0.000	0.000	0.000	0.004	0.000	0.000	-0.000	0.005	0.007
WR	0.705	0.707	0.926	0.696	0.912	1.007	0.678	0.672	0.841	0.795

Table 10. This table presents the pooled OLS regression results for the difference in monthly log return between the SEO firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each SEO firm is matched with a firm whose size (market capitalization) is between 70% and 130% of the SEO firm and has the closest book-to-market ratio at the end of the latest December prior to the SEO. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

In Columns 2 to 8, we control for variation in individual firm characteristics. Momentum, illiquidity, and idiosyncratic volatility are individually positively and significantly associated with abnormal returns, while size and BM are individually negatively associated with abnormal returns. The significance of the coefficient related to firm size and BM, even in a sample generated by matching based on these characteristics, emphasizes the value of incorporating temporal changes in the matching variables.

The estimated intercept remains statistically significant in Columns 2, 4, 7, and 8, indicating that the firm characteristics included in these Columns – beta, BM, idiosyncratic volatility, and investment – do not individually fully explain the negative abnormal performance of SEO firms. However, the estimated intercept is economically and statistically insignificant in Columns 3 and 5. Surprisingly, differences in either size or return momentum, explain about three-quarters of long-run abnormal returns to SEO firms rendering the remaining underperformance insignificantly different from zero. When including illiquidity as the only control variable in Column 6, the intercept is zero to three digits followed by one (corresponding to a wealth relative of 1.007), and statistically insignificant with a t-statistic of 0.048. Hence, we show that differences in illiquidity alone can explain all the apparent long-run abnormal returns to SEO firms.

In Column 9 we include all seven characteristics simultaneously, leading to significant coefficient estimates of size, momentum, BM, and investment, with investment being the only variable negatively associated with abnormal returns. Most important, the estimated intercept increases to -0.29% in this specification and is economically and statistically insignificant with a t-statistic of -1.138. In other words, we fail to reject the null hypothesis in Eq. (7), meaning that the significant linear relations between abnormal returns and four of the firm characteristics fully explain the apparent abnormal returns to firms that completed SEOs during the 1980 to 2017 sample period.

Column 10 of Table 8 reports the pooled OLS regressions results when allowing for non-linear relations between SEO firm characteristics and abnormal returns. As in the case of IPOs and bidding firms, adding the squared terms barely changes the estimated coefficients on each of the level terms. The estimated intercept in the non-linear specification remains statistically (t-statistic is -1.027) insignificant. After controlling for differences in firm characteristics, we, therefore, fail to reject the null hypothesis in Eq. (7) also in the non-linear specification. Variations in firm characteristics can fully explain the apparent abnormal returns to SEO firms.

5.3 The Calendar Time Portfolio Method

As we have discussed in Section 2.1, results regarding the long-run performance of event firms often conflict depending on methodology. We investigate the results from our modified BHAR method and CTP method when each is implemented in our 1980 to 2017 sample. Table 11 reports our key results when applying the CTP method, through estimating Eq. (8).

	IPO **(1)**	M&A **(2)**	SEO **(3)**
The calendar time portfolio method			
Dependent variable: Excess portfolio return			
MKT	1.0114***	0.9730***	1.1802***
	(35.012)	(58.781)	(44.534)
SMB	1.0748***	0.4718***	1.0204***
	(24.900)	(19.107)	(25.767)
HML	-0.2950***	0.3514***	-0.1535***
	(-6.987)	(14.529)	(-3.964)
UMD	-0.2963***	-0.2421***	-0.2335***
	(-10.171)	(-14.437)	(-8.735)
$Jensen's\ Alpha$	0.0011	0.0002	-0.0020*
	(0.845)	(0.251)	(-1.750)
$Observations$	516	514	509
$Adjusted\ R^2$	0.854	0.912	0.885

Table 11. This table presents the estimation results using the calendar time portfolio method, in which the dependent variable is the average return of a portfolio of firms that have conducted a certain type of corporate event during the past 60 months minus the risk-free rate, and the independent variables are the Fama and French three factors augmented with Carhart's momentum factor (Bessembinder and Zhang, 2013). All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

Most tests using the CTP method study simple returns, and this study is no different. It is widely known, that mean simple returns exceed mean log returns as a positive function of return variances (Bessembinder et al., 2019). Consequently, the larger return volatilities observed for event firms imply that these firms are expected to outperform control firms when considering simple returns rather than log returns. In Table 5, we report the average difference in the standard deviation for event firms versus their matched control firms in the 60 months after corporate events. The results indicate that returns to event firms are more volatile (positive standard deviation) than returns to control firms in the case of all three events. Since these are firms with negative average BHARs, it explains why the measured abnormal returns become less negative or even positive when we study simple returns subsequent to IPOs, M&As, and SEOs.

Furthermore, we observe that the FFC4 factors are all statistically significant at the 1% significance level across all three events, indicating that the four factors considered here are significantly associated with abnormal portfolio returns for the three corporate events. However, the estimated alpha is statistically insignificant for IPO and M&A firms, with t-statistics being 0.845 and 0.251 respectively. Since Jensen's Alpha through CTP corresponds to the constant obtained in Column 1 through BHAR, Table 11 illustrates that the BHAR and CTP methods often produce contradicting results. While we successfully reject the null hypothesis in Eq. (7) in the former method, we fail to do so in the latter method. The results mean that BHAR indicates negative long-run abnormal returns following IPOs and M&As, while the CTP method indicates an absence of abnormal returns for the two events. That is, the FFC4 factors considered here, fully explain abnormal returns to IPO and bidding firms.

While Bessembinder and Zhang (2013) use a sample period of 1980-2005, we extend this sample period with an additional 12 years and obtain deviating results for our sample of SEOs. That is, we find significant abnormal portfolio returns for our SEO sample when utilizing the CTP method (at the 10% significance level with a t-statistic of -1.750). Therefore, we argue that there is no apparent reason to believe that allowing for variations in firm characteristics (BHAR) necessarily leads to the same conclusion regarding abnormal returns as when allowing for factor risk (CTP). Rather, it could be sample-specific reasons behind the empirical results presented here.

It is important to note that our study does not advocate for a specific preference between studying simple (as in typical CTP studies) or log returns (as implicit in BHAR studies) when examining abnormal performance. Instead, our objective is to demonstrate that the choice between studying simple returns and log returns can lead to divergent conclusions regarding the presence and drivers of abnormal returns. This is evident from the substantial differences in return volatility between event firms and their matched firms, as reported in Table 5. We prove Fama (1998) right in saying that ‘a reasonable change of models often causes an anomaly to disappear’. Hence, the anomaly found using the BHAR approach may not be interpreted as much evidence for market inefficiency. On the other hand, our results for IPOs and M&As showcase a reason to believe that much of the tension between the traditional BHAR method and the CTP method indeed can be resolved by allowing the former method for imperfect control matching. However, the tension cannot be fully resolved.

5.4 Examining the Imperfect Relationship Between BHAR and CTP

The results presented so far highlight two important regularities. First, the conclusions from Bessembinder and Zhang (2013) mainly persist in our updated sample. Second, they illustrate that both, the BHAR and CTP, are imperfect models. Therefore, in this subsection, we aim to perform additional tests and consider alternative strategies and explanations to examine what causes this imperfection, in addition to flawed control firm matching and the use of simple versus log returns. This section aims to provide an answer to our second research question: *Can modifications to the BHAR and CTP methods help reconcile the contradicting outcomes regarding long-run abnormal returns?*

5.4.1 Equal Weight on Events vs. Equal Weight on Time Periods

We report the Fama and Macbeth estimation results of the same model specification as defined in Eq. (4), for all three event samples.

Column 11 of Table 12 reports the results of the Fama and Macbeth estimation results for our sample of IPO firms. We observe that placing equal weight on each time period does not notably affect the estimated coefficients obtained in the pooled OLS regression. Different from before is that all estimated coefficients are statistically insignificant. However, our variable of interest, the estimated intercept, is both economically (0.27%) and statistically (t-statistic is 0.154) insignificant in the Fama and Macbeth regression, consistent with the pooled non-linear specification in Column 10. This indicates that placing equal weight on each time period does not alter our initial conclusion, precisely that variation in firm characteristics fully explains the apparent abnormal returns to IPO firms.

	OLS (9)	OLS (10)	Fama-Macbeth (11)
IPOs			
Dependent variable: Difference in log returns			
$\Delta Beta$	-0.0207***	-0.0186***	-0.0283
	(-5.768)	(-5.500)	(-0.231)
$\Delta Beta^2$		-0.0108	-0.0473
		(-1.551)	(-0.215)
$\Delta Size$	0.0117***	0.0040	-0.0022
	(2.792)	(0.907)	(-0.012)
$\Delta Size^2$		0.0005	0.0030
		(0.079)	(0.010)
ΔBM	-0.0141***	-0.0136***	-0.0232
	(-4.061)	(-3.642)	(-0.137)
ΔBM^2		-0.0240***	-0.0371
		(-3.457)	(-0.129)
$\Delta Momentum$	0.0252***	0.0273***	0.0215
	(8.384)	(8.795)	(0.183)
$\Delta Momentum^2$		0.0722***	0.0715
		(13.337)	(0.329)
$\Delta Illiquidity$	-0.0074*	-0.0044	-0.0276
	(-1.932)	(-1.185)	(-0.102)
$\Delta Illiquidity^2$		-0.0396***	-0.0889
		(-7.025)	(-0.254)
$\Delta Idio.volatility$	-0.0238***	-0.0224***	-0.0281
	(-4.504)	(-4.352)	(-0.215)
$\Delta Idio.volatility^2$		-0.0415***	0.0157
		(-4.838)	(0.072)
$\Delta Investment$	-0.0003	-0.0032	0.0080
	(-0.102)	(-1.034)	(0.076)
$\Delta Investment^2$		-0.0038	-0.0049
		(-0.662)	(-0.025)
Constant	-0.0072*	0.0084	0.0270
	(-1.641)	(1.374)	(0.154)
Cluster by date	Yes	Yes	No
Observations	31 108	31 108	29 899
Adjusted R^2	0.011	0.020	0.054
WR	0.649	1.660	5.053

Table 12. This table presents the pooled OLS and Fama and Macbeth regression results for the difference in monthly log return between the IPO firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each IPO firm is matched with the firm having the closest but greater size (market capitalization) at the end of the earliest December after the IPO. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

For bidding firms in M&As, Column 11 of Table 13 reports results that correspond to those in Column 10, except that estimation is by the Fama and MacBeth method. The estimated intercept in this Column is economically (-1.04%) and statistically (t-statistic is -0.113) insignificant. The Fama and Macbeth regression, as for the pooled OLS regression, provides evidence that variations in firm characteristics are able to fully explain the abnormal returns to bidding firms. Finally, Column 11 of Table 14, reports results obtained by the Fama and Macbeth procedure for SEO firms. Like in the case of IPO firms and bidding firms, the estimated intercept is both economically (-0.28%) and statistically (t-statistic is -0.026) insignificant in Column 11. Differences in firm characteristics are able to fully explain the abnormal return to SEO firms in the linear specification, but also in the non-linear specification, regardless of whether we place equal weight on events or equal weight on each time period.

	OLS	OLS	Fama-Macbeth
	(9)	**(10)**	**(11)**
M&As			
Dependent variable: Difference in log returns			
$\Delta Beta$	-0.0048*	-0.0030	-0.0014
	(-1.732)	(-1.071)	(-0.024)
$\Delta Beta^2$		-0.0048	-0.0063
		(-1.019)	(-0.073)
$\Delta Size$	-0.0000	-0.0028	0.0031
	(-0.029)	(-1.073)	(0.053)
$\Delta Size^2$		0.0098***	0.0177
		(2.585)	(0.187)
ΔBM	-0.0031	-0.0029	-0.0036
	(-1.478)	(-1.379)	(-0.073)
ΔBM^2		0.0040	0.0153
		(1.072)	(0.145)
$\Delta Momentum$	0.0132***	0.0128***	0.0127
	(6.741)	(6.643)	(0.242)
$\Delta Momentum^2$		0.0188***	0.0186
		(4.950)	(0.231)
$\Delta Illiquidity$	-0.0075***	-0.0061***	-0.0025
	(-3.137)	(-2.575)	(-0.040)
$\Delta Illiquidity^2$		-0.0165***	-0.0167
		(-4.642)	(-0.169)
$\Delta Idio.volatility$	-0.0128***	-0.0116***	-0.0154
	(-4.436)	(-4.282)	(-0.240)
$\Delta Idio.volatility^2$		-0.0285***	-0.0245
		(-5.699)	(-0.237)
$\Delta Investment$	-0.0145***	-0.0143***	-0.0077
	(-6.362)	(-6.476)	(-0.137)
$\Delta Investment^2$		-0.0082**	-0.0020
		(-2.314)	(-0.023)
Constant	-0.0118***	-0.0035	-0.0104
	(-3.693)	(-0.836)	(-0.113)
Cluster by date	Yes	Yes	No
Observations	37 740	37 740	37 116
Adjusted R^2	0.005	0.009	0.046
WR	0.494	0.812	0.536

Table 13. This table presents the pooled OLS and Fama-Macbeth regression results for the difference in monthly log return between the bidding firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each bidding firm is matched with a firm whose size (market capitalization) is between 70% and 130% of the bidding firm and has the closest book-to-market ratio at the end of the latest December prior to the merger. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

	OLS	OLS	Fama-Macbeth
	(9)	**(10)**	**(11)**
SEOs			
Dependent variable: Difference in log returns			
$\Delta Beta$	-0.0020	-0.0024	0.0017
	(-1.013)	(-1.147)	(0.032)
$\Delta Beta^2$		-0.0027	-0.0065
		(-0.708)	(-0.071)
$\Delta Size$	0.0019***	-0.0004	-0.0022
	(0.902)	(-0.193)	(-0.039)
$\Delta Size^2$		-0.0067**	-0.0122
		(-2.119)	(-0.133)
ΔBM	0.0050**	0.0061***	0.0086
	(2.369)	(2.899)	(0.148)
ΔBM^2		-0.0071**	0.0029
		(-2.002)	(0.028)
$\Delta Momentum$	0.0220***	0.0225***	0.0233
	(11.492)	(11.173)	(0.388)
$\Delta Momentum^2$		0.0261***	0.0323
		(6.999)	(0.281)
$\Delta Illiquidity$	-0.0017	-0.0023	0.0089
	(-0.830)	(-1.111)	(0.141)
$\Delta Illiquidity^2$		-0.0097***	0.0035
		(-2.891)	(0.030)
$\Delta Idio.volatility$	0.0022	0.0034	-0.0024
	(0.955)	(1.480)	(-0.040)
$\Delta Idio.volatility^2$		-0.0051	-0.0029
		(-1.410)	(-0.022)
$\Delta Investment$	-0.0029*	-0.0033*	0.0043
	(-1.708)	(-1.939)	(0.079)
$\Delta Investment^2$		0.0078**	0.0140
		(2.417)	(0.152)
$Constant$	-0.0029	-0.0038	-0.0028
	(-1.138)	(-1.027)	(-0.026)
$Cluster\ by\ date$	Yes	Yes	No
$Observations$	41 820	41 820	41 520
$Adjusted\ R^2$	0.005	0.007	0.035
WR	0.841	0.795	0.845

Table 14. This table presents the pooled OLS and Fama and Macbeth regression results for the difference in monthly log return between the SEO firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each SEO firm is matched with a firm whose size (market capitalization) is between 70% and 130% of the SEO firm and has the closest book-to-market ratio at the end of the latest December prior to the SEO. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

In summary, our results provide evidence in opposition to Fama (1998) and Loughran and Ritter (2000). We conclude that the results found for IPO, bidding, and SEO firms in Section 5.2 are robust to the alternative of weighting each time period equally. The results obtained through our modified BHAR method, across all three events, reconcile the diverging results between pooled OLS regressions and Fama and Macbeth regressions. That is, both the pooled OLS and Fama-MacBeth specifications provide results consistent with the reasoning that long-run abnormal returns to IPO, bidding, and SEO firms over the 1980 to 2017 period can be fully explained by differences in firm characteristics. This amplifies the initial relationship found between our modified BHAR method and the CTP method. The divergence in results across BHAR and CTP is more attributable to the imperfect matching of event and control firms than to the implicit weighting of events.

5.4.2 Time-Invariant Firm Characteristics vs. Omitted Firm Characteristics

Following Bessembinder and Zhang (2013), the firm characteristics for event firms are all measured at the end of the month before the corporate event and take the same value across the 60 months after the corporate event in regressions[16].

Table 15 reports the results obtained by OLS estimation, with and without allowance for non-linear effects for the bidding sample. We observe that beta, size, BM, momentum, and investment measured prior to the merger are statistically significantly associated with long-run abnormal returns across both model specifications. This finding provides support for the idea that excluding relevant characteristics plays a significant role in explaining long-term abnormal returns, even in the absence of time variation in these characteristics. Our results indicate that failing to include these characteristics in analyses can lead to an incomplete understanding of the drivers behind long-term abnormal returns. In other words, the exclusion of these factors could potentially result in misleading conclusions about the factors influencing investment performance.

Different from before, the estimated intercept remains statistically (t-statistic is -9.326) significant in Column 10, when allowing for possible non-linear effects of bidding firm characteristics on long-run abnormal returns. This is in strong contrast to our initial findings for bidding firms in Section 5.2, indicating that differences in firm characteristics measured before the merger are not able to fully explain the abnormal returns to bidding firms.

[16] This analysis excludes IPOs as no pre-event data is available before the time of listing.

	OLS (1)	OLS (9)	OLS (10)
M&As			
Dependent variable: Difference in log returns			
$\Delta Beta$		-0.0135***	-0.0190***
		(-7.890)	(-6.439)
$\Delta Beta^2$			0.0158***
			(6.511)
$\Delta Size$		-0.0197***	-0.0194***
		(-9.307)	(-9.243)
$\Delta Size^2$			-0.0186***
			(-7.472)
ΔBM		0.0131***	0.0127***
		(10.048)	(9.362)
ΔBM^2			0.0163***
			(7.429)
$\Delta Momentum$		0.0080***	0.0098***
		(4.726)	(5.954)
$\Delta Momentum^2$			-0.0041*
			(1.821)
$\Delta Illiquidity$		-0.0013	-0.0008
		(-0.814)	(-0.459)
$\Delta Illiquidity^2$			0.0165***
			(7.881)
$\Delta Idio.volatility$		-0.0013	-0.0034
		(-0.545)	(-1.538)
$\Delta Idio.volatility^2$			-0.0095**
			(-2.480)
$\Delta Investment$		-0.0199***	-0.0113***
		(-7.703)	(-7.645)
$\Delta Investment^2$			--0.0074***
			(-3.535)
Constant	-0.0238***	-0.0239***	-0.0271***
	(-7.933)	(-7.525)	(-9.326)
Cluster by date	Yes	Yes	Yes
Observations	118 380	75 480	75 480
Adjusted R^2	0.000	0.011	0.013
WR	0.240	0.239	0.197

Table 15. This table presents the pooled OLS regression results for the difference in monthly log return between the bidding firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each bidding firm is matched with a firm whose size (market capitalization) is between 70% and 130% of the event firm and has the closest book-to-market ratio at the end of the latest December prior to the SEO. Wealth relative is calculated as exponential of sixty times the estimated intercept. The seven firm characteristics are all measured at the end of the month prior to the corporate event and take the same value across the sixty months after the corporate event in the regressions. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

Table 16 presents the estimated results of Eq. (3) and Eq. (4) obtained by OLS for the SEO sample. Beta, size, BM, momentum, idiosyncratic volatility, and investment measured prior to the equity offering have significant explanatory power for long-run abnormal returns to SEO firms in both model specifications. Most important, the estimated intercept is both economically and statistically significant across Columns 1 – 10. The results indicate that, regardless of model specification, differences in firm characteristics measured before the SEO are not able to fully explain the apparent abnormal returns to SEO firms. These results strongly contradict our findings in Section 5.2, in which we found that differences in firm characteristics fully explained long-run abnormal returns to SEO firms even in the linear specification.

	OLS (1)	OLS (9)	OLS (10)
SEOs			
Dependent variable: Difference in log returns			
$\Delta Beta$		0.0029**	0.0034***
		(2.409)	(2.780)
$\Delta Beta^2$			0.0010
			(0.444)
$\Delta Size$		-0.0111***	-0.0123***
		(-8.925)	(-9.723)
$\Delta Size^2$			-0.0236***
			(-11.079)
ΔBM		0.0133***	0.0124***
		(13.297)	(-12.113)
ΔBM^2			0.0161***
			(9.626)
$\Delta Momentum$		0.0139***	0.0132***
		(12.250)	(-12.174)
$\Delta Momentum^2$			0.0245***
			(10.602)
$\Delta Illiquidity$		0.0023*	0.0003
		(1.704)	(0.224)
$\Delta Illiquidity^2$			0.0028
			(1.423)
$\Delta Idio.volatility$		0.0070***	0.0055***
		(4.205)	(3.346)
$\Delta Idio.volatility^2$			0.0018
			(0.792)
$\Delta Investment$		-0.0081***	-0.0068***
		(-7.493)	(-6.496)
$\Delta Investment^2$			-0.0212***
			(-11.960)
Constant	-0.0058**	-0.0090***	-0.0092***
	(-2.328)	(-3.619)	(-2.907)
Cluster by date	Yes	Yes	Yes
Observations	216 420	109 140	109 140
Adjusted R^2	-0.000	0.006	0.011
WR	0.705	0.582	0.575

Table 16. This table presents the pooled OLS regression results for the difference in monthly log return between the SEO firm and their matched comparable firm. As in Bessembinder and Zhang (2013), each SEO firm is matched with a firm whose size (market capitalization) is between 70% and 130% of the event firm and has the closest book-to-market ratio at the end of the latest December prior to the merger. Wealth relative is calculated as exponential of sixty times the estimated intercept. The seven firm characteristics are all measured at the end of the month prior to the corporate event and take the same value across the sixty months after the corporate event in the regressions. Wealth relative is calculated as exponential of sixty times the estimated intercept. All model specifications employ robust standard errors. The associated t-statistics are reported in the parentheses below each coefficient. Superscripts ***, **, and * correspond to statistical significance at the one, five, and ten percent levels, respectively.

Concludingly, we provide evidence to support the notion that beta, size, momentum, and investment measured prior to the event month do have explanatory power for long-run abnormal returns to bidding and SEO firms. Moreover, the estimated coefficient on the BM ratio is statistically significant in both model specifications for both events. This implies that Fama (1998)'s discussion of imperfect event-date matches on the BM variable is relevant in describing long-run abnormal returns. We find that there are significant abnormal long-run returns to bidding and SEO firms that cannot be fully explained by time-invariant firm characteristics, while the opposite is true when allowing for variation in firm characteristics on a monthly basis. These results are essential as they showcase the importance of modifying the BHAR method to control for variation in firm characteristics over time. Especially since the presented Figures 1 – 3 demonstrate varying trends over time in median firm characteristics between event and control firms, allowing for such time variation, even in matching variables, remains desirable for two reasons. First, to fully explain long-run abnormal returns to event firms. Second, to largely reconcile the inconsistency in results between the modified BHAR method and the CTP method.

5.4.3 Value-Weighting the Portfolio Return in the CTP Approach

For each event, we follow Fama (1998) in weighting the monthly portfolio return by the number of event firms within the given portfolio. Table 17 presents the results.

	IPO	M&A	SEO
	(1)	**(2)**	**(3)**
The calendar time portfolio method			
Dependent variable: Excess portfolio return			
MKT	0.6636***	0.4924***	1.1361***
	(16.516)	(25.032)	(29.527)
SMB	0.8552***	0.2580***	1.1679***
	(14.244)	(8.793)	(20.313)
HML	-0.4920***	0.0825***	-0.1806***
	(-8.377)	(2.869)	(-3.212)
UMD	-0.1897***	-0.2081***	-0.3031***
	(-4.681)	(-10.441)	(-7.812)
$Jensen's\ Alpha$	-0.0008	-0.0013	-0.0027
	(-0.449)	(-1.513)	(-1.591)
$Observations$	516	514	516
$Adjusted\ R^2$	0.635	0.684	0.794

Table 17. This table presents the estimation results using the calendar time portfolio method, in which the dependent variable is the return of a portfolio of firms that have conducted a certain type of corporate event during the past 60 months minus the risk-free rate, and the independent variables are the Fama and French three factors augmented with Carhart's momentum factor (Bessembinder and Zhang, 2013). Testing the CTP approach for robustness, we follow Fama (1998) in weighting the monthly portfolio return by the number of event firms therein.

Like before, the FFC4 factors are all statistically significant at the 1% level, indicating that they have significant explanatory power for abnormal returns to IPOs, bidding firms, and SEOs. However, we observe that the estimated alpha is economically and statistically insignificant across all three events, with t-statistics ranging from -1.591 to -0.449. Value weighting the portfolio returns not only retains our initial observation, that the CTP method indicates an absence of abnormal returns for IPO and bidding firms. Rather, the gap between BHAR and CTP become greater, as we are not able to detect abnormal returns, even for our sample of SEOs. By following Fama's (1998) suggestion and value-weighting the monthly portfolio return by the number of event firms therein, the conflicting result in the present sample between the BHAR and CTP methods cannot be solved. The absence of an IPO-M&A-SEO anomaly and the apparent diversion between BHAR and CTP does not seem to be caused by excessive weight on tiny firms in the latter approach.

5.4.4 Allowing for Heteroscedasticity in the CTP Approach

To address the issue of the equal-weighted time problem, an alternative solution is to enhance the CTP method to allow for heteroskedasticity of the portfolio's abnormal return. This is necessary due to variations in the portfolio's composition over time. Drawing inspiration from the works of Jaffe (1974) and Mandelker (1974), we modify the approach by dividing the abnormal portfolio return for each month by its statistical precision. Table 18 presents the results.

	IPO	M&A	SEO
	(1)	**(2)**	**(3)**
The calendar time portfolio method			
Dependent variable: Excess portfolio return			
MKT	5.4001***	7.9883***	7.2945***
	(35.274)	(19.476)	(35.542)
SMB	4.6457***	4.4533***	5.0684***
	(20.350)	(7.346)	(16.515)
HML	-0.9626***	3.8628***	-0.6879**
	(-4.304)	(6.496)	(-2.293)
UMD	-0.4082***	-1.5913***	0.2095
	(-2.639)	(-3.838)	(1.012)
$Jensen's\ Alpha$	-0.0215***	-0.0021	-0.0432***
	(-3.202)	(-0.120)	(-4.787)
$Observations$	515	511	516
$Adjusted\ R^2$	0.825	0.534	0.803

Table 18. This table presents the estimation results using the calendar time portfolio method, in which the dependent variable is the return of a portfolio of firms that have conducted a certain type of corporate event during the past 60 months minus the risk-free rate, and the independent variables are the Fama and French three factors augmented with Carhart's momentum factor (Bessembinder and Zhang , 2013). Testing the CTP

approach for robustness, we follow Jaffe (1974) and Mandelker (1974) in dividing the abnormal portfolio return for each month by an estimate of its standard deviation.

We observe that most of the slope coefficients and their corresponding t-statistics have inflated substantially. By dividing the abnormal portfolio returns by their standard deviation, we implicitly assume that the volatility of the portfolio varies over time. However, if the volatility varies across different time periods, the scaling operation can distort the relationship between the variables and lead to inflated coefficients and t-statistics. They remain statistically significant across all three events. The exception is Carhart's momentum factor which now is statistically insignificant (t-statistic is -0.368) and has no explanatory power for abnormal SEO returns. Most important, the estimated alpha becomes statistically significant at the 1% level for IPO and SEO firms, with t-statistics of -3.202 and -4.787, respectively. When conducting a robustness test by weighting each month's portfolio return to account for heteroscedasticity, and obtaining a significant intercept, it suggests that our returns data for IPO and SEO firms exhibit heteroscedasticity. The exclusion of this feature previously led to biased standard errors of the estimated coefficients and incorrect inferences in Section 5.3.

By dividing the monthly portfolio returns by an estimate of its standard deviation, we are effectively normalizing the returns, giving more weight to months with lower volatility and less weight to months with higher volatility. The significant intercept obtained after implementing this weighting procedure implies that our modified CTP approach addresses the issue of heteroscedasticity and effectively captures an average excess return for IPOs and SEOs beyond what can be explained by the FFC4 factors included in the model. We provide striking evidence that the diverging results across the BHAR and CTP methods can largely be solved by allowing for heteroscedastic returns in the latter approach.

6. Conclusion

In many studies of long-run abnormal returns, researchers often deem it plausible to credit the abnormal returns to one of two things. First, entirely to the event itself, or second, to inadequate models for measuring expected returns. This is referred to as the 'bad model' problem (Fama, 1998). On the back of this, our paper addressed two key questions. First, whether the abnormal returns can be ascribed to the differences across event and control firms in characteristics that have been shown to be relevant for returns in the broader stock markets. Second, whether modifications to different methods used to measure abnormal returns can help reconcile the conflicting outcomes observed in long-run anomalies.

To study this, we evaluated abnormal returns by examining the intercept obtained through two popular approaches within the area of long-run event studies. First, we employed a refined version of the BHAR method, following Bessembinder and Zhang (2013), by conducting a regression analysis of differences in monthly log returns across event and matched non-event (control) firms on normalized differences in seven specific firm characteristics. Second, we utilized the CTP approach which formed a monthly portfolio of event firms and estimated the alpha of the portfolio against the Fama-French-Carhart four-factor model.

Our results proved that the key findings from Bessembinder and Zhang (2013), persisted in our updated sample. Specifically, we showed that long-run mean abnormal returns appeared negative for firms engaging in IPOs, M&As, and SEOs, which underperformed their matched counterparts by 56.5%, 76%, and 29.5% respectively. However, allowing for differences between event and control firms in market beta, firm size, BM, return momentum, illiquidity, idiosyncratic volatility, and capital investment, explained essentially all the apparent abnormal returns to event firms during the 1980 to 2017 period. For IPO and bidding firms, this conclusion was true only when our OLS estimations allowed for non-linear relations between event firm characteristics and stock returns, but regardless of whether results were weighted equally across events (pooled OLS regression) or equally across time (Fama-Macbeth regression). For our SEO sample, we found that variations in firm characteristics, independent of weighting strategy, fully explained abnormal returns to SEO firms even in the linear specification.

While our results regarding these three corporate events are important, they must be viewed critically. While the BHAR method indicated negative abnormal returns following IPOs, M&As, and SEOs, the CTP approach strikingly indicated an absence of abnormal returns for two of the events. Therefore, the findings from our modified BHAR method largely bridged the gap between the BHAR and CTP approaches and limited the 'bad model' problem. The results indicated that the divergence in results across the two methods is more attributable to the imperfect matching of event and control firms rather than to the implicit weighting of events. However, the results were only reconciled when implementing time-variant variables, highlighting the importance of refining the BHAR method to allow for variations in firm characteristics over time.

Our modified versions of the CTP method showed that the apparent inconsistency across BHAR and CTP may be largely resolved by allowing for heteroscedasticity in the latter approach. The above-mentioned results indicate that small tweaks to the BHAR and CTP methods could significantly change the conclusions drawn regarding long-run abnormal returns. Therefore, we cannot vouch for one of the methods, exclusively. Rather, we provide evidence consistent with Fama (1998) who states that long-term return anomalies are fragile and tend to vary substantially with reasonable changes in how they are measured.

In other words, the 'bad model' problem is unavoidable and apparent anomalies may be methodological illusions. Although our findings of abnormal returns should not be viewed as much evidence against market efficiency, our findings consistently support the conclusion that the apparent abnormal long-term returns observed in firms undergoing IPOs, M&As, and SEOs can be predominantly explained by the observable characteristics of these firms. Utilizing a simple set of just seven observable characteristics was as effective or more effective than prior more complex characteristic-based models in explaining abnormal stock returns. However, we do not steer clear of the 'bad model' problem. It would be intriguing to see whether future research can find a point, where the number of characteristics and the degree of the 'bad model' problem offset each other. There is an everlasting search for balance between the simplicity of a model and its ability to accurately capture and explain the observed abnormal returns.

Appendix A

This Appendix shows the step-to-step extraction process of event firms from SDC Platinum. Please note that Thomson's Financial SDC database is updated daily. Therefore, the number of event firms the reader obtains may differ slightly from what is reported in this thesis.

IPOs

Step 1 Select the Global New Issues Database

- In the Database Selection window, select Global New Issues Databases > Common Stock

Step 2 Specify the Offer Date Range

- In the Offer Date window, type 1980-2005

Step 3 Select IPOs

- Click on IPO Flag
- Accept the default, Select All IPOs

Step 4 Select U.S. Companies

- Click on Deal Type
- Select U.S. Common Stock (C)
- Click on Issuer/Borrower nation
- Deselect U.S.

Step 5 Exclude Real Estate Investment Trusts

- Click on All SIC
- Exclude Real Estate Investment Trusts (SIC code 6798)

Step 6 Exclude Closed-End Funds

- Click on Closed-End Fund/Trust flag
- Select Exclude Closed-End Fund/Trust

Step 7 Exclude American Depositary Receipts

- Click on Security Type
- Exclude American Depositary Receipts (SEC code 804)

M&As

Step 1 Select the M&A Database

- From the Database Selection window Mergers & Acquisitions tab, select US Targets

Step 2 Specify an Announcement Date

- In the Announcement Date window, type 1980-2005

Step 3 Select Public U.S. Companies

- Click on acquirer and target public status
- Select Public (P)

Step 4 Select All Completed Transactions

- Click on Deal Status
- Select Completed (C) and Unconditional (U)

Step 5 Select U.S. Events

- Click on Target and Acquiror nation
- Deselect U.S.[17]

Step 6 Select the Relevant Form of M&A

- Click on Deal Form
- Select AP, AM, AR, M

Step 7 Select Disclosed and Undisclosed Value Mergers and Acquisitions

- Click on Deal Type
- Select Disclosed and Undisclosed Value Mergers & Acquisitions

Step 8 Exclude Minority Stake Purchases:

- Click on Deal Type
- Exclude Minority Stake Purchases

Step 9 Select a Deal Value:

- Click on Deal Value ($ Mil)
- In the LO text box type 5, in the HI text box accept the default, HI.

SEOs

Step 1 Select the Global New Issues Database

- In the Database Selection window, select Global New Issues Databases > Common Stock

Step 2 Specify the Offer Date Range

- In the Offer Date window, type 1980-2005

Step 3 Select SEOs

- Click on Issue Type

[17] Within the SDC database, the U.S. is found under "America" and "North America". The correct way to select the U.S. is to highlight all countries available in SDC, deselect the U.S., and click "Exclude". This way, we are able to select the U.S. as the only nation of interest.

- Select Follow-On[18] (FO)

Step 4 Select U.S. Companies

- Click on Deal Type
- Select U.S. Common Stock (C)
- Click on Issuer/Borrower nation
- Deselect U.S.

Step 5 Exclude Financial Companies

- Click on All SIC
- Exclude all companies with SIC codes between 6000-6999

Step 6 Exclude Public Utilities

- Click on All SIC
- Exclude all companies with SIC codes between 4900-4999

Step 7 Exclude Global Depositary Receipts

- Click on Security Type
- Exclude Global Depositary Receipts (SIC code 8330)

Step 8 Exclude American Depositary Receipts

- Click on Security Type
- Exclude American Depositary Receipts (SIC code 804)

Step 9 Exclude Unit Offerings

- Click on Unit Issue Flag
- Select exclude Unit Issues

[18] Note that we select follow-on offerings and not secondary offerings. This is because all follow-on offerings are seasoned equity offerings, while all secondary offerings may not be seasoned equity offerings.

Appendix B

While the information on events is retrieved from SDC Platinum, the firms' financial data needed for our analysis is retrieved from CRSP and Compustat within the WRDS database. However, problems are commonly reported when merging two different databases. Merging the two databases requires a common identifier. The company identifiers SDC Platinum provided are CUSIPs, unique identification numbers assigned to stocks. While CRSP can take CUSIPs as input, the CUSIPs are unfortunately not permanent. Therefore, when directly transferring the CUSIPs from SDC Platinum to CRSP we lose about half of our observations since CUSIP changes over time. Also, CUSIPs are reassignable to other firms, meaning that using CUSIPs may result in analyzing a firm that was not in our initial sample.

We avoid this problem by using a permanent identifier (which is not reassignable even after delisting or defaulting). For each event firm's CUSIP obtained from SDC platinum, we convert this into its corresponding PERMNO, using a conversion tool provided by CRSP. Observations are lost in this step, as all CUSIPs do not have PERMNOs. Furthermore, we also need accounting data for event firms from Compustat. Challenges are commonly reported when merging CRSP and Compustat within the WRDS database. To optimally do this, we use the PERMNOs in the CRSP/Compustat merged database. In doing so, we have been able to merge SDC Platinum and WRDS, obtaining a permanent identifier for the companies where this is possible, and which have all the financial data that is needed for our analysis. Simply put, the following procedure is utilized:

Step 1

- Extract Event Firms from SDC and Their Associated 6-digit CUSIPs

Step 2

- Log Into the WRDS Database and Select the 'CRSP' Vendor

Step 3

- Under 'Annual Update', Click on 'Tools'

Step 4

- Convert the 6-digit CUSIPs Into Their Corresponding PERMNOs

Step 5

- Utilize the PERMNOs from Step 4 to Extract Firms' Financial Data

References

Agrawal, A, Jaffe, J. & Mandelker, G. (1992). The Post-Merger Performance of Acquiring Firms: A Re-examination of an Anomaly. *Journal of Finance,* 47(4), 1605-1621. https://doi.org/10.1111/j.1540-6261.1992.tb04674.x

Amihud, Y. & Mendelson, H. (1986). Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics*, 17(2), 223-249. https://doi.org/10.1016/0304-405X(86)90065-6

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets*, 5(1), 31-56. https://doi.org/10.1016/S1386-4181(01)00024-6

Amihud, Y., Hameed, A., Kang, W. & Zhang, H. (2015). The Illiquidity Premium: International Evidence. *Journal of Financial Economics*, 117(2), 350-368. https://doi.org/10.1016/j.jfineco.2015.04.005

Ang, A., Hodrick, R., Xing, Y. & Zhang, X. (2006). The Cross-Section of Volatility and Expected Returns. *Journal of Finance*, 61(1), 259-299. https://doi.org/10.1111/j.1540-6261.2006.00836.x

Asparouhova, E., Bessembinder, H. & Kalcheva, I. (2010). Liquidity Biases in Asset Pricing Tests. *Journal of Financial Economics*, 96(2), 215-237. https://doi.org/10.1016/j.jfineco.2009.12.011

Asquith, P. (1983). Merger Bids, Uncertainty, and Stockholder Returns. *Journal of Finance*, 11(1-4), 51-83. https://doi.org/10.1016/0304-405X(83)90005-3

Bali, T. G., Brown, S. J. & Tang, Y. (2017). A Lottery-Demand-Based Explanation of the Beta Anomaly. *Journal of Financial and Quantitative Analysis*, 52(6), 2369-2397. https://doi.org/10.1017/S0022109017000928

Banz, R. W. (1981). The Relationship Between Return and Market Value of Common Stocks. *Journal of Financial Economics*, 9(1), 3-18. https://doi.org/10.1016/0304-405X(81)90018-0

Barber B. & Lyon, J. (1997). Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics. *Journal of Financial Economics*, 43(3), 341-372. https://doi.org/10.1016/S0304-405X(96)00890-2

Betton, S., Eckbo, E., Thorburn, K. (2008). Corporate Takeovers. In: Eckbo, E. (Ed.). *Handbook of Corporate Finance: Empirical Corporate Finance, Vol. II. , Elsevier/North- Holland*, Amsterdam, 15, 291–429.

Bessembinder, H. & Zhang, F. (2013). Firm Characteristics and Long-Run Stock Returns After Corporate Events. *Journal of Finance*, 109(1), 83-102. https://doi.org/10.1016/j.jfineco.2013.02.009

Bessembinder, H., Cooper, M. & Zhang, F. (2019). Characteristic-Based Benchmark Returns and Corporate Events. *The Review of Financial Studies*, 32(1), 75–125. https://doi.org/10.1093/rfs/hhy037

Boehme, D. R. & Sorescu, M. S. (2002). The Long-Run Performance Following Dividend Initiations and Resumptions: Underreaction or Product of Chance? *Journal of Finance*, 57(2), 871-900. https://doi.org/10.1111/1540-6261.00445

Brav, A. & Gompers, P. A. (1997). Myth or Reality? The Long-Run Underperformance of Initial Public Offerings: Evidence from Venture and Nonventure Capital-Backed Companies. *Journal of Finance*, 52(5), 1791-1821. https://doi.org/10.1111/j.1540-6261.1997.tb02742.x

Brav, A., Geczy, C. & Gompers, P. A. (2000). Is the Abnormal Return Following Equity Issuances Anomalous? *Journal of Financial Economics*, 56(2), 209-249. https://doi.org/10.1016/S0304-405X(00)00040-4

Brennan, M. J. & Subrahmanyam, A. (1996). Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns. *Journal of Financial Economics*, 41(3), 441-464. https://doi.org/10.1016/0304-405X(95)00870-K

Butler, A. W. & Wan, H. (2010). Stock Market Liquidity and the Lon-Run Stock Performance of Debt Issuers. The Review of Financial Studies, 23(11), 3966-3995. https://doi.org/10.1093/rfs/hhq082

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1), 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Cochrane, J. H. (2011). Presidential Address: Discount Rates. Journal of Finance, 66(4), 1047-1108. https://doi.org/10.1111/j.1540-6261.2011.01671.x

Damodaran, A. (2012). *Investment valuation: Tools and techniques for determining the value of any asset* (3. ed.). Wiley.

Eckbo, B. E., Masulis, R. W. & Norli, Ø. (2000). Seasoned Public Offerings: Resolution of the 'New Issues Puzzle'. *Journal of Financial Economics*, 56(2), 251-291. https://doi.org/10.1016/S0304-405X(00)00041-6

Eckbo, B. E., Masulis, R. W. & Norli, Ø. (2007). Corporate Takeovers. In: Eckbo, E. (Ed.). *Handbook of Corporate Finance: Empirical Corporate Finance, Vol. II., Elsevier/North- Holland*, Amsterdam, 1, 233-373.

Fama, E. F., Fisher, L., Jensen, M. C & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, 10(1), 1-21. https://doi.org/10.2307/2525569

Fama, E. F. & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3). https://doi.org/10.1086/260061

Fama, E. F. & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F. & French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F. & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. *Journal of Finance*, 50(1), 131-155. https://doi.org/10.1111/j.1540-6261.1995.tb05169.x

Fama, E. F. (1998). Market efficiency, Long-Term Returns, and Behavioral Finance. *Journal of Financial Economics*, 49(3), 283-306. https://doi.org/10.1016/S0304-405X(98)00026-9

Fama, E. F. & French, K. R. (2008). Dissecting Anomalies. *Journal of Finance*, 63(4), 1653-1678. https://doi.org/10.1111/j.1540-6261.2008.01371.x

Flannery, M. J. & Rangan, K. P. (2006). Partial Adjustment Toward Target Capital Structures. *Journal of Financial Economics*, 79(3), 469-506. https://doi.org/10.1016/j.jfineco.2005.03.004

Freyberger, J., Neuhierl, A. & Weber, M. (2017). Dissecting Characteristics Nonparametrically. *The Review of Financial Studies*, 33(5), 2326-2377. https://doi.org/10.1093/rfs/hhz123

Green, J., Hand, J. R. M. & Zhang, X. F. (2017). The Characteristics that Provide Independent Information About Average U.S. Monthly Stock Returns. *The Review of Financial Studies*, 30(12), 4389-4436. https://doi.org/10.1093/rfs/hhx019

Harford, J. (2005). What Drives Merger Waves? *Journal of Financial Economics*, 77(3), 529-560. https://doi.org/10.1016/j.jfineco.2004.05.004

Harvey, C. R., Liu, Y., & Zhu, H. (2015). … and the Cross–Section of Returns. *Review of Financial Studies*, 29(1), 5-68. https://doi.org/10.1093/rfs/hhv059

Haugen, R. A. & Baker, N. L. (1996). Commonality in the Determinants of Expected Stock Returns. *Journal of Financial Economics*, 41(3), 401-439. https://doi.org/10.1016/0304-405X(95)00868-F

Hou, K., Karolyi, A. & Kho, B. (2011). What Factors Drive Global Stock Returns? The Review of Financial Studies, 24(8), 2527-2574. https://doi.org/10.1093/rfs/hhr013

Ibbotson, R. G. (1975). Price Performance of Common Stock New Issues. *Journal of Financial Economics*, 2(3), 235-272. https://doi.org/10.1016/0304-405X(75)90015-X

Ikenberry, D., Lakonishok, J. & Vermaelen, T. (1995). Market Underreaction to Open Market Share Repurchases. *Journal of Financial Economics*, 39(2-3), 181-208. https://doi.org/10.1016/0304-405X(95)00826-Z

Jaffe, J. F. (1974). Special Information and Insider Trading. Journal of Business, 47(3), 410-428. http://www.jstor.org/stable/2352458

Jegadeesh, N. & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1), 65-91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jensen, T. I., Kelly, B. T. & Pedersen, L. H. (2021). Is There A Replication Crisis in Finance? National Bureau of Economic Research. https://doi.org/10.3386/w28432

Kelly, B. T., Pruitt, S. & Su, Y. (2019). Characteristics are Covariances: A Unified Model of Risk and Return. *Journal of Financial Economics*, 134(3), 501-524. https://doi.org/10.1016/j.jfineco.2019.05.001

Kenneth R. French Data Library (2021). *Data library*. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Loughran, T. & Ritter, J. (1995). The New Issues Puzzle. *Journal of Finance*, 50(1), 23-51. https://doi.org/10.1111/j.1540-6261.1995.tb05166.x

Loughran, T. & Vijh, A. (1997). Do Long-Term Shareholders Benefit From Corporate Acquisitions? *Journal of Finance*, 52(5), 1765-1790. https://doi.org/10.1111/j.1540-6261.1997.tb02741.x.

Loughran, T. & Ritter, J. (2000). Uniformly Least Powerful Tests of Market Efficiency. *Journal of Financial Economics*, 55(3), 361-389. https://doi.org/10.1016/S0304-405X(99)00054-9

Lyandres, E., Le, S. & Zhang, L. (2008). The New Issues Puzzle: Testing the Investment-Based Explanation. *The Review of Financial Studies*, 21(6), 2825-2855. https://doi.org/10.1093/rfs/hhm058

Lyon, J. D., Barber, B. M. & Tsai, C. (1999). Improved Methods for Tests of Long-Run Abnormal Stock Returns. *Journal of Finance*, 54(1), 165-201. https://doi.org/10.1111/0022-1082.00101

Mandelker, G. (1974). Risk and Return: The Case of Merging Firms. Journal of Financial Economics, 1(4), 303-335. https://doi.org/10.1016/0304-405X(74)90012-9

Mitchell, M. L. & Stafford, E. (2000). Managerial Decisions and Long-Term Stock Price Performance. Journal of Business, 73(3), 287-329. https://doi.org/10.1086/209645

Mitchell, M., Pulvino, T. & Stafford, E. (2005). Price Pressure around Mergers. *Journal of Finance*, 59(1), 31-63. https://doi.org/10.1111/j.1540-6261.2004.00626.x

Moeller, S. B., Schlingemann, F. P. & Stulz, R. M. (2005). Wealth Destruction on a Massive Scale? A Study of Acquiring-Firm Returns in the Recent Merger Wave. *Journal of Finance*, 60(2), 757-782. https://doi.org/10.1111/j.1540-6261.2005.00745.x

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, 22(1), 435-480. https://doi.org/10.1093/rfs/hhn053

Rau, P. R., & Vermaelen, T. (1998). Glamour, Value, and the Post-Acquisition Performance of Acquiring Firms. *Journal of Financial Economics*, 49(2), 223-253. https://doi.org/10.1016/S0304-405X(98)00023-3

Ritter, J. R. & Welch. I. (2002). A Review of IPO Activity, Pricing, and Allocations. *Journal of Finance*, 57(4), 1795-1828. https://doi.org/10.1111/1540-6261.00478

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance*, 19(3), 425-442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Spiess, K. D. & Affleck-Graves, J. (1995). Underperformance in Long-Run Stock Returns Following Seasoned Equity Offerings. *Journal of Financial Economics*, 38(3), 243-267. https://doi.org/10.1016/0304-405X(94)00817-K

Titman, S., (Wei, KCJ) & Xie, FX. (2004). Capital Investments and Stock Returns. *Journal of Financial and Quantitative Analysis*, 39(4), 677-700. https://doi.org/10.1017/S0022109000003173