Which, why, and for how long do IPOs underperform?*

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Abstract

Based on a sample of 7,378 firms going public in the 1975-2005 period, we document a significant underperformance of IPO firms over the first year after going public, while there is virtually no underperformance thereafter. Moreover, by decomposing the Carhart-alpha we find that IPO underperformance, where present, is mainly due to fundamental differences in firm characteristics (e.g., market-to-book ratio, leverage, and R&D expenditures scaled by sales) between IPO companies and more seasoned, non-issuing firms. In fact, our results indicate that IPO firms neither perform materially better nor worse than mature companies with similar firm characteristics. Finally, we show that IPO underperformance is partially predictable. IPOs associated with overly optimistic growth prospects (and correspondingly high valuation levels) and IPOs going public during hot issue periods perform substantially worse than other IPOs.

Keywords: IPO underperformance, anomaly, long-term performance evaluation

JEL classification: G3, G12, C21

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1 Introduction

There is an ongoing debate on whether or not the stocks of IPO firms underperform in the long-term. Ritter (1991) and Loughran and Ritter (1995, 2000), for example, document strong underperformance of IPOs over a five-year period following the issue date. In contrast, Brav and Gompers (1997), Brav, Geczy, and Gompers (2000), and Gompers and Lerner (2003) show that IPO firms are strongly tilted towards small and high-growth companies which has been the worst-performing investment style over the last several decades. Hence, the latter studies conclude that by controlling for size and the book-to-market ratio, IPO firms do not perform worse than similar non-issuing companies.

This paper contributes to this debate by showing that IPO underperformance is highly dependent on the definition of "IPO firms". By analyzing a sample of 7,378 IPOs in the U.S. taking place from 1975 through 2005 and relying on a Carhart (1997) type four factor model, we find clear evidence for IPO underperformance when "IPO firms" are defined as companies going public within the last year. However, there is no significant IPO underperformance beyond two years after going public.

Several explanations for the apparent IPO underperformance have been brought forward in prior research. Eckbo and Norli (2005), for example, argue that IPO underperformance is mainly due to the IPO firms' high stock turnover and low leverage ratios. Once they account for these two factors in their estimations, IPO underperformance disappears. Another explanation for IPO underperformance is provided by Loughran and Ritter (1995). Their results indicate that the stocks of firms going public in so-called 'hot' markets (i.e., in periods of particularly high IPO activity) tend to perform substantially worse than the stocks of companies going public in 'cold' markets (i.e., in periods with low IPO activity). They argue that IPO firms might try to take advantage of transitory windows of opportunity by going public during hot issue markets when their stock is substantially overvalued. In line with this, Purnanandam and Swaminathan (2004) find IPOs to be overvalued at the offer price. Correspondingly, they argue that the poor long-term performance of IPOs is mainly due to the fact that on average the high growth expectations implicit in the initial valuation fail to materialize.

However, there is a shared commonality in prior research on IPO long-term performance: Lacking an appropriate methodological framework, the analysis is necessarily one-dimensional. We overcome this shortcoming by relying on two different *multivariate* methodologies. Both of them ensure that the statistical results are heteroscedasticity consistent and robust to very general forms of cross-sectional and temporal dependence. On the one hand, we examine five-year buy-and-hold abnormal returns (BHARs) by aid of Jegadeesh and Karceski's (2004) robust version of the BHAR approach. As a methodological contribution, we propose a regression-based extension of their technique which enables us to include multivariate explanatory variables in the analysis. On the other hand, we analyze the determinants of IPO-performance by relying on a recent variant of the calendar time portfolio approach (or Jensen's alpha approach). Specifically, we employ Hoechle and Zimmermann's (2007) "GCT-regression model" which enables us to decompose the Carhart-alpha into firm specific components.[1]

We use the multivariate BHAR-analysis to explore *which* of the firm characteristics known by the time of the IPO are good predictors for the IPO firms' subsequent performance. Our key results indicate that IPOs associated with overly optimistic growth prospects (and correspondingly high valuation levels) tend to perform worse than IPOs for which growth expectations are more modest. In addition, we find firms going public in hot issue periods to underperform over the long-run. Both these findings are consistent with Loughran and Ritter's (1995) 'transitory windows of opportunity' explanation.

In order to investigate *why* IPOs underperform in the long-run, we base our analysis on Hoechle and Zimmermann's (2007) generalization of the calendar time portfolio approach. Considering a comprehensive set of firm characteristics, we cannot identify a simple explanation for IPO underperformance. In particular, our results indicate that no single firm characteristic can explain why the stocks of IPO firms tend to underperform during the first year after the

[1]Hoechle and Zimmermann (2007) show that it is possible to perfectly reproduce the results of the traditional calendar time portfolio approach by estimating a firm-level pooled OLS (or WLS) regression with Driscoll and Kraay (1998) standard errors. Their GCT-regression model generalizes the traditional calendar time portfolio approach in the sense that it allows for the inclusion of firm-specific characteristics in the analysis.

going public. However, we find that IPO underperformance can be explained by a combination of some of the most prominent explanatory approaches from prior research. Specifically, by decomposing the Carhart-alpha into firm characteristics related to the IPO market environment, leverage and liquidity, firm valuation, corporate diversification strategies, and investments, we find no significant differences between the performance of IPO firms and that of non-issuing (mature) companies. This result withstands a battery of robustness checks including a truncation of the sample period, restricting the sample to Nasdaq companies, and addressing potential linking problems between the CRSP and COMPUSTAT databases.

We therefore conclude that the documented IPO underperformance is mainly the result of fundamental differences in firm characteristics between IPO and more seasoned non-issuing firms. However, when over time the characteristics of IPO firms converge to those of the more seasoned companies, the same holds true for the stock returns and the apparent underperformance of IPO firms vanishes. As a consequence, the results from our GCT-regression analysis are in line with the findings of Brav and Gompers (1997), Brav, Geczy, and Gompers (2000), and Eckbo and Norli (2005) and suggest that one should be careful with speaking of an IPO underperformance 'anomaly'.

The remainder of the paper proceeds as follows. Section 2 presents the sample selection criteria, the data, and the algorithms used to match IPO firms to seasoned non-issuing firms. The descriptive analysis is in Section 3. Section 4 examines which IPOs underperform in the long-run by analyzing buy-and-hold abnormal returns. Section 5 addresses the question of why IPOs underperform in the long-term. Here, statistical inferences are based on the generalized calendar time portfolio approach. Section 6 concludes.

2 Data

2.1 Sample selection

Our sample data stems from three sources. First, our IPO sample is derived from an updated version of the Field-Ritter dataset of company founding dates as used in Field and Karpoff (2002) and Loughran and Ritter (2004). The dataset includes a list of 8,309 firms going public in the U.S. from 1975 through 2005.[2] Second, we use the complete Center for Research in Security Prices (CRSP) database to obtain information on monthly stock prices and returns of issuing and non-issuing firms. Third and finally, we complement our sample data with quarterly firm characteristics from the COMPUSTAT/CRSP merged database.[3]

To obtain our final IPO sample, we exclude from the original Field-Ritter dataset all 761 IPOs that are classified as ADRs, closed-end funds, unit trusts, REITs, partnerships, banks, and savings and loans (S&Ls). We also drop two duplicate observations and 168 firms for which the first month containing security prices in CRSP does not coincide with the IPO-month in the Field-Ritter dataset. After applying all these filters, we end up with a final sample of 7,378 IPOs.

When preparing the CRSP and COMPUSTAT data, we also exclude all ADRs, closed-end funds, unit trusts, REITs, partnerships, banks, and savings and loans (S&Ls). In addition, for all companies not being part of our final IPO sample we drop the first five years of CRSP and COMPUSTAT data. This helps us to ensure that companies not contained in the IPO list are mature and therefore do not dilute our statistical inferences presented in Sections 4 and 5. Our final dataset comprises a total of 14,562 firms of which 7,378 went public between 1975 and 2005 and the remaining 7,184 companies are at least 5 years old when they appear in our sample.

[2]The dataset is available from `http://bear.cba.ufl.edu/ritter/ipodata.htm`

[3]For the link between CRSP and COMPUSTAT, we require that the fiscal period end date must be within the link date range. Moreover, we set USEDFLAG=1 and allow for link types LU, LC, LN, and LO. See the 'CRSP/Compustat Merged Database Guide' for details.

2.2 Matching IPO firms with non-issuing control firms

Following earlier studies (e.g., Ritter, 1991; Loughran and Ritter, 1995; Eckbo and Norli, 2005) we compare the characteristics and returns of IPO companies with those of mature control firms. In doing so, we select for each IPO firm a control firm whose IPO occurred more than 5 years earlier. The matching algorithm relies either on firm size (market capitalization) or on both size and the book-to-market ratio. The size-matched firm is the firm which is closest in market capitalization to the IPO firm at the end of the quarter in which the IPO takes place. When matching is based on both size and book-to-market ratio, respectively, we proceed in two steps. In the first step, we identify all firms whose market capitalization is within 30% of the IPO firm's market value at the end of the quarter in which the IPO takes place. From this subset we then define the matching firm to be the company whose book-to-market ratio is closest to but higher than that of the IPO firm.

When merging data from COMPUSTAT and CRSP, we noticed that the market capitalization figures provided by the two databases often differ by a non-negligible amount. Specifically, for 22% (14.5%) of the observations in our final sample, the quarterly market capitalization from COMPUSTAT differs by more than 5% (10%) from that in CRSP.[4] Because we cannot assess the reliability of the differing values which might in turn affect our results, we also perform a third, alternative matching procedure. Here, we begin by restricting our sample of IPOs and matching firms to the set of companies for which the quarterly market capitalization in CRSP and COMPUSTAT *never* differs by more than 5%. For the subset of these firms, we then replicate the size and book-to-market ratio based matching algorithm described above. Validating the link between CRSP and COMPUSTAT in this way reduces the number of IPO firms in our sample to 3,974 companies (as compared to 6,257 for the size and book-to-market based match when the link is not validated) going public in the U.S. from 1975 through 2005.

We keep the same matching firms until the end of the test period (in general five years) or

[4]Correspondingly, the 'CRSP/Compustat Merged Database Guide' states that "because of different identification conventions, universe, and available historical information between the two databases, linking is not a straightforward process."

until they are delisted, whichever occurs first. If a matching firm is delisted before the end of the test period, we choose a second (and, if necessary, a third, fourth, or fifth) matching firm and append the data from this replacement firm after the delisting of the previous matching firm. The replacement matching firms are identified on the original ranking date (i.e., at the end of the quarter in which the IPO takes place) and are based on the same selection procedures as the original matching firms. For example, the size-matched replacement firms are simply the firms second, third, fourth, and fifth closest in market capitalization to the IPO firm.

3 Descriptive Analysis

We begin our descriptive analysis by comparing the firm characteristics of IPOs with those of the matching firms in the (or at the end of the) quarter in which the IPO takes place. When comparing the IPO sample with the set of size-matched control firms in the first two columns of Table I, we find that the differences in the mean and median market capitalization of issuing and non-issuing companies are negligible. This confirms that our size-based matching algorithm works well.

More importantly, however, Table I indicates that the book value of equity is substantially lower for IPO firms than for the size-matched companies. Correspondingly, the market-to-book ratio of IPOs is almost twice as large as that for the control firms. On average, growth expectations are therefore much more optimistic for IPOs than for the size-matched companies. Together with the observation that mean and median sales of IPO firms are less than half as large as those of the control sample, the high market-to-book ratio of IPO companies confirms their growth-stock nature (e.g., Brav, Geczy, and Gompers, 2000). Moreover, both the book and market leverage ratios are substantially lower for IPO firms than for the size-matched companies. However, this is hardly surprising for at least two reasons: First, any issuance of equity is associated with a decrease in the leverage ratio (e.g., Alti, 2006) and second, IPO firms generally have fewer assets in place and lower current earnings to support extensive borrowing as compared to more mature firms (e.g., Eckbo and Norli, 2005). Finally, compared to their sales figures, IPO firms tend to undertake larger acquisitions and to engage in higher capital and R&D expenditures than non-issuing companies.[5]

In Columns 3 and 4, we alternatively compare the IPO firms with the set of size and book-to-market matched firms. Although the matching algorithm only targets at minimizing the differences in firm size and the book-to-market ratio between IPO and matching firms, the results indicate that the sales numbers of IPO and matching firms also conform much better than for the size-matched firms. Consequently, this approves that selecting the matching firms according to their size and book-to-market ratio indeed facilitates a better match between IPO firms and control firms with respect to the value-growth dimension. In addition, the differences in all other firm characteristics between IPO and matching firms also become smaller (with the exception of mean acquisitions per sales) indicating a universally better match. In Column 5, we additionally introduce the requirement of a verified link (based on the market capitalization) between the COMPUSTAT and CRSP databases as explained above. Interestingly, the results indicate that the differences between IPO and non-issuing matching firms become even smaller (with the exception of sales). Hence, by eliminating firms with potential data problems and/or a deficient link between the two databases, the non-issuing matching firms better match the IPO firms with respect to a number of different firm characteristics.

Recent research (e.g., Helwege and Liang, 2004; Alti, 2006) reveals that certain firm characteristics of companies going public in so-called 'hot' markets substantially differ from those of firms going public in 'cold' markets.[6] In addition, Loughran and Ritter (1995) and Helwege and Liang (2004) document substantially lower stock returns of hot as compared to cold market IPOs. Hot issue markets are characterized by an unusually high volume of offerings, severe

[5]As IPO firms exhibit substantially higher market-to-sales ratios than matching firms, we alternatively scale the CAPEX, R&D expenditures, and acquisitions figures by the firms' market capitalization instead of sales. Unreported results reveal that, in fact, the differences in all three variables between IPO and matching firms disappear. Hence, when scaled by the market value, IPO and matching firms are very similar in respect of their capital and R&D expenditures as well as the volume of their acquisitions.

[6]The theoretical underpinnings for this recent empirical strand of literature are provided by signaling and other asymmetric information models (e.g., Allen and Faulhaber, 1989), models that explain the choice between going public or remaining private (e.g., Pastor and Veronesi, 2005), and behavioral finance models based on investor irrationality (e.g., Teoh, Welch, and Wong, 1998). For a survey of this literature we refer to Helwege and Liang (2004).

underpricing, and frequent oversubscriptions of the offerings (e.g., Lowry and Schwert, 2002; Helwege and Liang, 2004). By contrast, cold issue markets are associated with substantially less and smaller IPOs, less underpricing, and fewer instances of oversubscriptions.

To examine potential differences amongst firms going public in different market-states, we split our IPO sample into three subsets based on whether the IPO took place in a hot, neutral, or cold market. In order to perform this classification, we first count for each quarter in the sample period the number of IPOs in our database. We then rank the quarters according to the number of IPOs and classify the quartile containing the quarters with the most IPOs as 'hot market', the bottom half as 'cold market', and the remaining quarters as 'neutral markets'.[7] Out of the 124 quarters in our sample period, 32 are classified as hot, 29 as neutral, and 63 as cold markets. This classification scheme translates into 4,206 IPOs being rated as hot market IPOs, 1,966 as neutral market IPOs, and 1,206 as cold market IPOs.

A comparison of firms going public in hot, neutral, and cold markets is provided in Columns 6 through 9 of Table I. By and large, the results are in line with those of Helwege and Liang (2004) and Alti (2006). Most importantly, the average (and median) IPO in a hot market is larger and exhibits a higher market-to-book ratio than in a neutral and cold market. Moreover, the book and market leverage ratios of hot market IPOs tend to be lower than those of neutral and cold market IPOs.

Figure 1 displays in event time the evolution of seven out of the nine firm characteristics reported in Table I. With the exception of acquisitions per sales (where mean values are reported), the figure contrasts the sample medians of the 7,378 IPO companies' firm characteristics with those of the matching firms. Consistent with the findings in Table I the figure reveals that at the end of the IPO quarter the firm characteristics of IPO companies differ substantially from those of the non-issuing matching firms. Moreover, it is evident that the respective differences are smaller for matching algorithms that are based on both size and the market-to-book ratio as compared to a matching algorithm relying exclusively on size. Finally, the figure shows that the

[7] Helwege and Liang (2004), for example, use a similar procedure to define hot, cold, and neutral markets. However, they use monthly data and classify their sample months into hot, neutral, and cold markets based on three-month centered moving averages of the number of IPOs.

differences between the firm characteristics of IPO companies and those of the matched firms decline over time and become relatively small five years after the IPO (the usual time horizon used in long-term IPO studies) and even more so 12 years after the IPO.

Summarizing, the results of Table I and Figure 1 reveal that IPO firms differ from more mature companies with respect to a number of different firm characteristics. Provided that some of these fundamental characteristics are related to stock returns, they might play an important role in explaining *why* the stocks of IPO firms perform differently from those of more mature companies. Indeed, there is a large body of empirical literature that has established strong cross-sectional relationships between some of these firm characteristics and stock returns. Interestingly, however, our results show that the fundamental characteristics of IPO firms converge to those of the more seasoned control firms over time. Consequently, we would expect that performance differences between IPO firms and more mature companies are particularly pronounced shortly after the IPO but then start withering.

4 Buy-and-Hold Abnormal Returns (BHARs)

In this section, we investigate whether there are firm characteristics known by the time of the IPO which possess predictive power for the IPO companies' subsequent performance. In doing so, we rely on an analysis of buy-and-hold abnormal returns (BHARs). These are known to better reflect actual investment experiences of investors than other approaches which involve periodic rebalancing to measure risk-adjusted performance. Moreover, the analysis of BHARs also facilitates a comparison of our results with the findings of prior studies (e.g., Loughran and Ritter, 1995; Eckbo and Norli, 2005). When drawing statistical inferences from buy-and-hold abnormal returns, Kothari and Warner (2007) recommend to rely on the Jegadeesh and Karceski (2004, henceforth JK) tests since they perform quite well in both random and non-random (industry) samples, respectively. Correspondingly, we base our statistical inferences on JK's "HSC_t" statistic. However, as a theoretical contribution we show how to reproduce the HSC_t statistic by aid of a linear regression with Driscoll and Kraay (1998) standard errors.

Hence, it is straightforward to generalize JK's robust version of the BHAR approach such that it allows for the inclusion of firm specific explanatory variables in the analysis.

4.1 Statistical inference for buy-and-hold abnormal returns

The H-month buy-and-hold abnormal return (BHAR) for the i-th firm ($i = 1, ..., N$) going public in month t ($t = 1, ..., T$) is defined as

$$AR_{it} = R_{it}^{IPO} - R_{it}^{Match} = \prod_{\tau=t}^{t+H-1} \left(1 + R_{it,\tau}^{IPO}\right) - \prod_{\tau=t}^{t+H-1} \left(1 + R_{it,\tau}^{Match}\right) \tag{1}$$

where $R_{it}^{k} = \prod_{\tau=t}^{t+H-1} \left(1 + R_{it,\tau}^{k}\right)$ refers to the H-month buy-and-hold return of the i-th IPO company ($k = IPO$) and its matching firm ($k = Match$) and $R_{it,\tau}^{k}$ denotes the firms' month τ return. Emanating from the average BHAR for all firms going public in month t,

$$AR_t = \begin{cases} N_t^{-1} \sum_{i=1}^{N_t} AR_{it} \ , & \text{if } N_t > 0 \\ 0 \ , & \text{otherwise} \end{cases} , \tag{2}$$

one obtains the average buy-and-hold abnormal return for all $N = \sum_{t=1}^{T} N_t$ IPO firms in the sample as

$$\overline{AR} = \sum_{t=1}^{T} w_t AR_t = \mathbf{w}'\mathbf{A} \tag{3}$$

where we stack the frequency weights $w_t = N_t/N$ in vector $\mathbf{w}' = [\begin{array}{ccc} w_1 & \cdots & w_T \end{array}]$ and store the monthly averages of the abnormal returns in vector $\mathbf{A}' = [\begin{array}{ccc} AR_1 & \cdots & AR_T \end{array}]$.

Provided that the buy-and-hold abnormal returns are independently and normally distributed, one can test for $\overline{AR}$ being different from zero by performing a conventional t-test:

$$\hat{t} = \frac{\overline{AR}}{\hat{\sigma}\left(\overline{AR}\right)} \overset{as}{\sim} N(0,1) \tag{4}$$

with $\hat{\sigma}\left(\overline{AR}\right) = \sqrt{\frac{1}{N}\frac{1}{N-1}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\left(AR_{it} - \overline{AR}\right)^2}$. However, in light of the much-debated hot-issue phenomenon reported in the IPO literature, it has to be expected that the H-month buy-and-hold abnormal return of a firm going public in month t is correlated with the BHAR of a firm going public in month $t + j$ (with $1 \leq |j| \leq H - 1$) due to an overlap in the holding period. Therefore, the independence assumption underlying the conventional t-statistic in (4) seems to be rather inappropriate.

To account for likely cross-sectional dependence amongst the BHAR of firms going public in month t and $t+j$ (with $1 \leq |j| \leq H-1$), Jegadeesh and Karceski (2004) suggest to estimate the standard deviation of $\overline{AR}$ in (4) as

$$\hat{\sigma}\left(\overline{AR}\right) = \sqrt{\mathbf{w}'\hat{\mathbf{\Omega}}\mathbf{w}} \tag{5}$$

where the kj^{th} element $\hat{\phi}^u_{kj}$ of the $T \times T$ covariance matrix $\hat{\mathbf{\Omega}}$ is estimated as

$$\hat{\phi}^u_{kj} = \begin{cases} (AR_k)^2 \ , & \text{if } \ k = j \\ AR_k AR_j \ , & \text{if } \ 1 \leq |k-j| \leq H-1 \\ 0 \ , & \text{otherwise} \end{cases} \tag{6}$$

The covariance matrix estimator in (6) is heteroscedasticity and autocorrelation (up to H-1 lags) consistent. Moreover, by relying on monthly averages of the abnormal returns, JK's covariance matrix estimator also controls for cross-sectional dependence amongst the BHARs. As a result, Jegadeesh and Karceski's (2004) HSC_t statistic allows for very robust statistical inference on buy-and-hold abnormal returns:[8]

$$HSC\_t = \frac{\overline{AR}}{\sqrt{\mathbf{w}'\hat{\mathbf{\Omega}}\mathbf{w}}} \overset{as}{\sim} N(0,1) \tag{7}$$

In contrast to the conventional variant of the BHAR-approach for which it is impossible to account for cross-sectional dependence, the subtle partition of the event firms into T monthly cohorts enables Jegadeesh and Karceski (2004) to ensure that statistical inference remains valid

[8]Note, however, that by examining the small sample properties of the HSC_t statistic, Jegadeesh and Karceski (2004) find that HSC_t tends to over-reject the null hypothesis of $\overline{AR} = 0$ if tabulated critical values are used. Therefore, they provide tables with empirical critical values that are derived from Monte Carlo simulations. However, in this paper we do not base our statistical inferences on empirical critical values. We rather rely on tabulated critical values since our IPO sample is much larger than the cases considered in JK's study.

even when cross-sectional dependence is present in the data. It is important to note that JK's approach essentially restores (parts of) the time-series information inherent in the dataset and it is this information advantage compared to the conventional version of the BHAR-approach which renders JK's long-run performance test heteroscedasticity consistent and robust to very general forms of cross-sectional and temporal dependence.

However, it is not evident why estimating covariance matrix $\mathbf{\Omega}$ according to (6) should produce more appropriate standard errors than estimating the kj^{th} element of $\mathbf{\Omega}$ by subtracting the sample mean as follows:

$$\hat{\phi}^{c}_{kj} = \begin{cases} \left(AR_k - \overline{AR}\right)^2 \ , & \text{if } \ k = j \\ \left(AR_k - \overline{AR}\right)\left(AR_j - \overline{AR}\right) \ , & \text{if } \ 1 \leq |k-j| \leq H-1 \\ 0 \ , & \text{otherwise} \end{cases} \tag{8}$$

Indeed, in a footnote Jegadeesh and Karceski (2004) write that "in unreported tests, we examined the performance of serial covariance estimators where we subtracted the sample means and the distribution of the test statistics were quite similar to those we report here."

4.2 Generalizing the BHAR approach

It is possible to replicate the centered version of JK's HSC_t statistic in (8) by estimating the following intercept-only regression with Driscoll and Kraay (1998) standard errors:[9]

$$AR_{it} = \alpha + \varepsilon_{it} \tag{9}$$

Specifically, in the appendix we formally prove the following proposition:

Proposition 1 *Estimating regression (9) with Driscoll-Kraay standard errors (which rely on rectangular rather than on Bartlett weights for the lags) reproduces Jegadeesh and Karceski's*

[9]Moreover, it is well-known in the statistics literature that estimating regression (9) with OLS standard errors replicates the t-statistic of the paired-sample mean comparison test in (4).

(2004) HSC_t statistic with the covariance matrix $\mathbf{\Omega}$ being estimated according to (8).

It is straightforward to generalize regression model (9) by including a set of M explanatory variables $x_{m,it}$ which may vary across both the time dimension and the cross-sectional dimension, respectively, as follows:

$$AR_{it} = \alpha + \sum_{m=1}^{M} \beta_m x_{m,it} + \varepsilon_{it} \tag{10}$$

Estimating regression (10) with Driscoll-Kraay standard errors allows for valid statistical inference even if the buy-and-hold abnormal returns are cross-sectionally dependent due to overlapping holding periods. As a result, regression (10) not only constitutes a natural generalization of Jegadeesh and Karceski's (2004) robust variant of the BHAR approach. More importantly, it is also a direct long-term event study analogue to the technique of regressing cumulative abnormal returns (CAR) on a set of explanatory variables which is commonly encountered in short-term event studies (e.g., see DeLong, 2001; Amihud and Li, 2006).

4.3 Traditional BHAR analysis

As it is standard in the literature, we calculate five-year buy-and-hold abnormal returns. Consequently, we exclude from the analysis all 491 IPOs taking place in the 2001-2005 period. In addition, we exclude 59 observations for which the size-matched BHAR exceeds 1500% in absolute value.[10] Hence, we are left over with a final sample of 6,828 firms going public from 1975 through 2000 upon which we base our BHAR-analysis.

Table II presents the results from the traditional (univariate) BHAR-analysis. Column 1 (All IPOs) reveals that on average the size-matched five-year BHAR amounts to -34.99% (Panel A). This figure is comparable to the corresponding buy-and-hold abnormal returns reported by Brav, Geczy, and Gompers (2000) and Eckbo and Norli (2005).[11] Moreover and consistent with

[10]Note that the exclusion of IPOs with extreme BHARs does not materially affect our results.

[11]Note that Brav, Geczy, and Gompers (2000) do not use individual matching firms to calculate the BHARs for their sample of 4,622 IPOs from 1975 through 1992. Instead, they define broad stock market indices such as

the aforementioned studies, we find the underperformance to be substantially reduced when matching is based on both size and the book-to-market ratio (Panel B). However, when we include the additional requirement of a validated link between CRSP and COMPUSTAT (Panel C), the average BHAR deteriorates again. Consequently, our results indicate that a linking problem between the CRSP and COMPUSTAT databases may to some extent be responsible for the apparently more favorable BHAR figures emanating from a size and book-to-market based matching procedure as compared to the BHARs obtained from a size only matching algorithm.

To assess the statistical significance of the buy-and-hold abnormal returns, Table II reports four alternative t-statistics: First, the "conventional" t-statistic is computed according to equation (4). Second, the "JK uncentered" t-statistic refers to Jegadeesh and Karceski's (2004) original HSC_t statistic in (7). Third, the "JK centered" t-statistic is the centered version of the HSC_t statistic. It is also computed according to formula (7). However, here we estimate $\hat{\Omega}$ according to the specification in (8). Fourth, the "DK" t-statistic is obtained from estimating the intercept only regression (9) with Driscoll and Kraay (1998) standard errors.

Most importantly, the results in Column 1 (All IPOs) provide further evidence for IPO underperformance. As such, the average five-year buy-and-hold abnormal return of IPO firms is negative and statistically significant at the 10% level or higher irrespective of the matching algorithm and the specification of the t-statistic. Moreover, for all three matching algorithms the conventional t-statistic is larger in absolute terms than the alternative t-statistics which are heteroscedasticity consistent and robust to cross-sectional and temporal dependence. This indicates that (erroneously) assuming independence amongst the IPO firms' buy-and-hold abnormal returns tends to overestimate actual t-statistics.[12]

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the S&P 500, Nasdaq Composite as well as the equal- and value-weighted CRSP indices as benchmarks.

[12]Of the robust t-statistics, JK's original HSC_t statistic is the most conservative by construction. It is followed by the centered version of the HSC_t statistic and the Driscoll-Kraay t-statistic. This ranking is deterministic since the variance estimate for the mean abnormal return based on (6) is at least as big as that obtained from relying on (8). Similarly, by being smaller than one the Bartlett weights are the reason why the variance estimate of the Driscoll-Kraay estimator is smaller than that of the centered HSC_t statistic which puts a unit weight on all the lags (see equations (A-3) and (A-5) in the appendix for details).

In IPO studies which rely on the BHAR-approach, it is common to control for the firms' market valuation and the incorporated growth expectations by relying on a matching procedure that accounts for both firm size and the book-to-market ratio. In order to cope with the potential importance of growth expectations for IPO performance, we investigate the relation between firm valuation and IPO long-term performance more thoroughly. In fact, our results will show that controlling for the book-to-market ratio does not fully capture growth expectations.

While the prior literature investigating the predictability of IPO long-term performance mainly focuses on underpricing[13] as an explanatory variable, Purnanandam and Swaminathan (2004) identify overvaluation at the offer price to be a reliable predictor for the long-term performance of IPOs. However, the valuation of IPO firms is treacherous for at least two reasons. First, Zheng (2007) claims that calculating value metrics based on accounting data prior to the IPO tends to overstate the valuation of issuing firms.[14] The second issue arises from the fact that valuation levels (and therefore growth expectations) may vary substantially between different industries (Hawawini, Subramanian, and Verdin, 2003). This is of particular importance for the valuation of IPO firms since they are often concentrated in a few industries (Helwege and Liang, 2004). However, a matching procedure relying on industry affiliation is problematic since for many industries there are only a few publicly traded companies with a market capitalization comparable to that of the IPO firms. Consequently, one specific non-issuing firm would often be matched with a large number of IPO firms (Loughran and Ritter, 1995).

We overcome these problems by using a similar approach as introduced by Berger and Ofek (1995) to estimate the valuation discount associated with corporate diversification strategies.

[13]The empirical evidence in these studies is controversial: While Ritter (1991), for example, finds that underpricing and long-term performance are negatively related, Krigman, Shaw, and Womack (1999) provide evidence for a positive relation. The model of Ljungqvist, Nanda, and Singh (2006) demonstrates that the relation is not necessarily monotonic. In particular, it predicts a negative relation only if the probability of a hot issue market coming to an end is small.

[14]Zheng (2007) criticizes the valuation method employed by Purnanandam and Swaminathan (2004). Most importantly, he argues that because many firms raise capital when going public, IPO firms are expected to increase their sales and earnings after the IPO. Since these expectations are reflected in the stock prices of IPO firms, it follows that the market capitalization of an IPO firm should be higher than that of a matching company with the same accounting data in the year prior to the IPO.

Specifically, we calculate an excess value measure (XVAL) which relates the firms' actual market value (MV_{it}) to their industry and sales adjusted imputed value (IMV_{it}^{j}) as follows:

$$\mathrm{XVAL}_{it} = \ln\left(\mathrm{MV}_{it}\right) - \ln\left(\mathrm{IMV}_{it}^{j}\right) \tag{11}$$

$$\text{where} \qquad \mathrm{IMV}_{it}^{j} = \mathrm{Sales}_{it} \times med\left(\mathrm{MVS}\right)_{jt},$$

Sales_{it} denotes the period t sales of firm i and $med\left(\mathrm{MVS}\right)_{jt}$ refers to the median market-to-sales ratio of all n_t firms which belong to the same industry j as firm i.[15] A negative (positive) value of the XVAL measure implies that the firm trades at a discount (premium). To prevent our analysis from being influenced by outliers, we follow Berger and Ofek (1995) in classifying XVAL as missing if its absolute value is bigger than 1.386 (i.e., if the excess value measure indicates a "misvaluation" of factor four and more). Of the 2,880 IPO firms with a missing XVAL by end of the quarter in which the IPO occurred, 1,574 in fact possess an excess value measure which is bigger than 1.386 in absolute terms.[16]

In Table II, Columns 2 to 4, we report the results for three sub-samples based on whether the IPO firms' excess value is smaller than zero (low-valued IPOs), larger than zero (high-valued IPOs), or missing by end of the quarter in which the IPO occurred. As expected, IPO firms exhibit a substantially higher median excess value than the size-matched firms. Interestingly, this finding also holds when matching is based on both size and the book-to-market ratio. More importantly, however, our results indicate that IPO firms with a low excess value measure experience substantially higher BHARs as compared to high-valued IPOs. This finding holds irrespective of the matching algorithm and the choice of the t-statistic. While the BHAR

[15]We compute the actual market value of a firm as the sum of the market value of equity plus the book value of debt. Furthermore, we follow Berger and Ofek (1995) and define a firm's industry as the narrowest SIC group with at least five mature (i.e., aged five years or more) companies. The imputed value for 68.7% of all sample firms is based on four-digit SIC codes, 21.2% on three-digit SIC codes, 9.6% on two-digit SIC codes, and 0.5% on one-digit SIC codes.

[16]The results presented in Table II remain qualitatively similar when XVAL measures in excess of ± 2.079 (i.e., a misvaluation of factor eight and more) are considered as missing or if no such restriction is implied. Moreover, we also follow Berger and Ofek (1995) in computing an excess value measure that is based on assets rather than on sales. However, the results are again qualitatively similar to those reported in Table II and thus are omitted from presentation.

of low-valued IPOs in Panel B (non-verified CRSP-COMPUSTAT link) is even positive, the average buy-and-hold abnormal return of low-valued IPOs is insignificant for all matching algorithms and t-statistics. In contrast, the average BHARs of high-valued firms are negative and statistically significant at the 5% level or higher when matching is based on firm size (Panel A) or size and the book-to-market ratio with a verified link between CRSP and COMPUSTAT (Panel C). The buy-and-hold abnormal returns for IPOs with a missing excess value measure (Column 4) are even lower than those for the high-valued IPOs (Column 3). Unreported tests show that this finding is not exclusively due to those firms with an absolute value of XVAL equal to or larger than 1.386. In fact, the average BHARs are similar for firms with a missing excess value measure and firms with an absolute value of XVAL equal to or larger than 1.386.[17]

Finally, in Column 5 of Table II we assess whether the difference between the BHAR of low- and high-valued IPOs is significantly different from zero. We do this by regressing the BHARs of the IPOs on a dummy variable which is equal to one if $-1.386 < \mathrm{XVAL} \leq 0$ and zero otherwise. Statistical inference is then based on the significance of the coefficient estimate for the dummy variable. While the difference of the two groups' buy-and-hold abnormal returns is positive for all matching algorithms, it is only significant (at the 5% level) when matching is based on size (Panel A). For the matching algorithms that rely on both size and the book-to-market ratio, the difference is at best marginally significant at the 10% level (Panels B and C).

In Figure 2, we present the evolution of the mean and median BHARs over the 60-month period subsequent to the going public. On average, the BHAR of an IPO firm is slightly positive in the first few months after the IPO but then starts decreasing for all three matching algorithms. Note that the initial increase in BHARs occurs although the IPOs' day zero returns are excluded. This pattern is consistent with price support by (lead) underwriters either through quoting the highest bid prices (e.g., Schultz and Zaman, 1994), providing favorable analyst rec-

[17]For example, the average BHAR for IPOs with $abs(\mathrm{XVAL}) > 1.386$ amounts to -63.87% when matching is based on firm size (1,574 observations), -30.99% when matching is based on size and the book-to-market ratio (1,561 observations), and -38.65% when matching is based on size and the book-to-market ratio (with verified CRSP-COMPUSTAT link; 1,024 observations). Complete results are available from the authors upon request.

ommendations (e.g., Michaely and Womack, 1999), or by using a combination of stabilizing bids, aftermarket short covering, and penalty bids to control flipping activities (e.g., Aggarwal, 2000). While the size-matched BHAR subsequently drops to about -35% after five years, the decline of the size and book-to-market matched BHARs is less pronounced.

Median BHARs are in general somewhat lower than the mean buy-and-hold abnormal returns. This reflects the often cited characteristic of IPOs as being long shot investments. More importantly, however, the median BHARs exhibit a steeply negative slope over the first one or two years which gradually flattens thereafter. Compared to the median size-matched BHARs, the flattening begins earlier and the IPO underperformance turns out to be less pronounced when matching is based on both size and the book-to-market ratio.

When comparing the evolution of BHARs amongst low- and high-valued IPOs in Figure 2, it is apparent that over the first 36 to 48 months low-valued IPOs outperform their high-valued counterparts. This result holds for all three matching algorithms and is mainly due to the poor performance of the high-valued IPOs. Accordingly, IPOs associated with overly optimistic growth prospects tend to perform worse than IPOs with more modest growth expectations.

4.4 Which IPOs do underperform?

In order to investigate the determinants of IPO long-run performance, we estimate several variants of regression (10) with Driscoll-Kraay standard errors.[18] In all regressions we use the IPO firms' five-year buy-and-hold abnormal return with respect to a size-matched non-issuing company as the dependent variable.[19] The explanatory variables are related to firm valuation, IPO market environment, leverage, organizational structure, and investment expenditures. Since all

[18]We base our statistical inferences on Driscoll and Kraay's (1998) nonparametric covariance matrix estimator since by relying on Bartlett weights the Driscoll-Kraay estimator assures positive semi-definiteness of the variance-covariance matrix (e.g., see Newey and West, 1987). By contrast, the Jegadeesh-Karceski estimator discussed above uses unit weights for the lags. It is therefore not assured that the variance-covariance matrix of the Jegadeesh-Karceski estimator is positive definite. This has consequences for the empirical work. In fact, many of the regressions reported in this section could not be estimated with Jegadeesh and Karceski's (2004) covariance matrix estimator because the variance-covariance matrix was non-invertible.

[19]The results remain qualitatively similar when we replace the size-matched five-year BHAR by the size and book-to-market matched BHAR (with or without verified CRSP-COMPUSTAT link).

explanatory variables refer to the firms' IPO quarter, the regressions estimated in this section are free from look-ahead bias problems.

In our first regression specification, we regress the BHARs on the industry- and sales-adjusted excess valuation measure (XVAL) described above. The results in Column 1 (Excess Valuation) of Table III are consistent with those in Table II and Figure 2. The coefficient estimate for XVAL is negative and significant at the 1% level indicating that IPOs for which exceptional growth opportunities are anticipated often do not manage to meet these high expectations and, as a consequence, perform worse than IPOs for which growth expectations are more modest.[20]

Next, we regress the buy-and-hold abnormal returns on the two dummy variables HOT and COLD being one for firms going public in hot and cold markets, respectively, and zero otherwise. Specifically, we want to investigate whether the issue period has an effect for the long-run performance. As explained in Section 3, Loughran and Ritter (1995) and Helwege and Liang (2004) document substantially lower stock returns of hot market IPOs than for cold market IPOs. However, the results in Column 2 (Issue period) reveal that neither the performance of hot nor that of cold market IPOs significantly differs from the performance of IPOs taking place in neutral issue periods.

Eckbo and Norli (2005) show that Nasdaq IPOs exhibit a significantly higher stock turnover and are less leveraged than non-issuing matching firms listed on the same exchange. The greater stock turnover may indicate a potential liquidity-based explanation for IPO underperformance. In addition, Eckbo and Norli (2005) argue that the relatively low leverage ratio of IPO firms might be important in explaining IPO underperformance as leverage has a "turbo charging" effect on the factor loadings in a multifactor model. Consequently, they expect IPO stocks to respond stronger to leverage-related risk factors such as the stock market return, credit spread, term spread, or unexpected inflation. To investigate their conjecture empirically, they estimate

[20]In an earlier study, Jain and Kini (1994) report evidence which is consistent with poor long-run IPO returns due to misvaluations at the time of going public. Specifically, they report that for 682 firms going public between 1976 and 1988 the median operating cash flow-to-assets ratio fell substantially between the year prior to going public and three years later. Hence, operating cash flows did not grow sufficiently to justify the excessive valuation levels at the time of the IPO.

a number of multifactor models including Carhart's (1997) four-factor model augmented with a liquidity-based risk factor and a seven-factor macro model where the size, book-to-market, and momentum factors are replaced with the liquidity-based factor and a set of five macroeconomic risk factors. Their results reveal that IPO firms exhibit significant factor loadings on these liquidity- and leverage-related factors. Most importantly, the alphas of their models are insignificant which indicates that IPO underperformance can be explained by their factor models.

Based on the findings of Eckbo and Norli (2005), Column 3 (Leverage) of Table III regresses the size-matched BHARs on the IPO firms' market leverage ratio.[21] The coefficient estimate is positive and significant at the 1% level indicating that IPOs with high leverage ratios outperform IPOs with low leverage ratios. However, it is important to notice that leverage is affected by the going public itself through the issuance of new equity and is likely to be adjusted subsequently. Such dynamic changes in firm characteristics cannot be captured in a BHAR-regression framework. As a result, it is important to bear in mind that the analysis of this section aims at identifying characteristics which are able to *predict* IPO long-run performance. By contrast, the GCT-regression model considered in Section 5 allows us to account for the dynamics in firm characteristics when investigating the reasons for long-term IPO underperformance.

Another potentially important factor which might be related to the IPO firms' performance is their organizational structure. In fact, a large body of research documents a conglomerate discount associated with running a multi-segment company.[22] Hence, organizational structure might to some extent explain IPO underperformance if, for example, the percentage of diversified firms is higher in the IPO sample than amongst the non-issuing matching firms. Moreover,

[21]We restrict the BHAR-analysis in this section to leverage and postpone the analysis of abnormal trading volume to the dynamic GCT-analysis presented in Section 5. The reason is that trading volume over the first quarter after the IPO is unlikely to be a meaningful measure of stock liquidity as it strongly depends on initial returns (e.g., Kaustia, 2004). In addition, Fernando, Krishnamurthy, and Spindt (2004) show that initial turnover is related to the IPO price level.

[22]e.g., see Lang and Stulz (1994) and Berger and Ofek (1995) for evidence on non-financial firms, Lins and Servaes (1999) for international evidence, and Laeven and Levine (2007) and Schmid and Walter (2007) for evidence on financial firms.

the valuation and performance consequences related to corporate diversification may differ between young firms and more seasoned companies. Therefore, as a next step, we regress the size-matched BHARs on dummy variable 'Diversified' which is one for firms with more than one segment in COMPUSTAT's Segments data file and zero otherwise. However, the results in Column 4 (Diversification) reveal no significant relation between IPO long-run performance and organizational structure at the time of the going public. One possible reason for this might be that diversified firms are substantially larger on average than focused firms while larger IPOs generally exhibit a better long-term performance as compared to small IPOs. Hence, we additionally control for firm size by including the log of the market capitalization but find the coefficient estimates on both firm size and Diversified to be insignificant (not tabulated).

In Column 5 (All (except expenditures)) we simultaneously control for the industry-adjusted excess value (XVAL), the issue period (HOT, COLD), market leverage (Leverage), and the organizational structure (Diversified). Most importantly, the negative effect of XVAL persists indicating that IPOs with high valuation levels tend to underperform IPOs which are comparably lower priced. In addition, the negative coefficient on HOT becomes significant at the 1% level. This finding is consistent with the results of Loughran and Ritter (1995) and Helwege and Liang (2004). Hence, firms going public in hot issue periods significantly underperform IPOs taking place in neutral markets over the subsequent five years once we control for firm valuation, leverage, and diversification. Finally, the effect of leverage becomes insignificant while there are no material changes to the coefficient estimates of the COLD and Diversified dummies as compared to Columns 2 and 4.

In a next step, we introduce four additional explanatory variables that are related to the IPO firms' investment expenditures during the IPO quarter. This allows us to investigate whether the IPO firms' investments in the quarter of going public affect their long-run performance. Specifically, we include in the regression the firms' capital expenditures scaled by sales (CAPEX), acquisitions scaled by sales (Acquisitions), and R&D expenditures scaled by sales (R&D) as explanatory variables. Since R&D is often missing, we replace missing values for R&D by zero but include a dummy variable in the regression which is set to one if R&D is missing (missR&D).[23] The results for the regression including the four explanatory variables related to the IPO firms' investment expenditures are reported in Column 6 (Expenditures). The estimates reveal that while high capital expenditures in the IPO quarter are, on average, associated with a poor performance over the subsequent five years, the opposite holds true for IPO firms not disclosing any R&D figures for the IPO quarter.

Finally, we estimate a regression model including all explanatory variables considered in this section. The results are presented in Column 7 (All) of Table III. Most importantly, the negative effect of XVAL persists which confirms our finding from Table II and Figure 2, namely that IPOs associated with overly optimistic growth prospects (and correspondingly high valuation levels) perform worse than IPOs for which growth expectations are more modest. In addition, the coefficient estimate for the HOT dummy remains negative and significant, indicating that firms going public in hot issue periods tend to underperform over the long-run. This result is consistent with the findings of Loughran and Ritter (1995) who argue that IPO firms might try to take advantage of transitory windows of opportunity by going public during hot issue markets when their stock is substantially overvalued. With the exception of missR&D and CAPEX, the coefficient estimates for all other explanatory variables are statistically insignificant.

However, due to the static nature of the (multivariate) BHAR-approach considered in this section, this method is only suited to examine whether or not a number of variables being known at the time of the IPO are capable to explain the subsequent performance of IPOs. Consequently, the analysis presented in this section aims at identifying firm characteristics which are able to predict IPO performance over the subsequent years. However, it is important to note that nothing can be said about the actual reasons for long-term IPO underperformance. In particular, the results from the traditional BHAR analysis should not be taken as evidence for an IPO underperformance 'anomaly' as the documented underperformance might just be

[23]Gompers, Ishii, and Metrick (2004) argue that replacing missing values for R&D by zero may be justified for the following reasons: First, there are only few observations in COMPUSTAT indicating a value of R&D equal to zero. This suggests that very small and negligible R&D expenditures or R&D expenditures equal to zero are often not reported at all. Second, firms which do not report R&D ratios are mainly from industries known for low R&D expenditures such as electric utilities, real estate firms, retailers, or financial services firms.

the result of an imperfect match between IPO companies and the control firms.

5 Generalized Calendar Time Portfolio Analysis

5.1 The GCT-regression model

In this section, we investigate *why* the stocks of IPO firms underperform those of more mature companies. In doing so, we rely on Hoechle and Zimmermann's (2007) "GCT-regression model" which allows us to decompose the Carhart-alpha into firm specific components. The GCT-regression model involves estimating on the firm level a pooled OLS regression with Driscoll and Kraay (1998) standard errors. Therefore, its estimation results are heteroscedasticity consistent and robust to very general forms of cross-sectional and temporal dependence.

In all GCT-regressions considered in this section, we regress the individual firms' quarterly excess return y_{it} on a set of explanatory variables. Specifically, we estimate pooled OLS regressions with the following structure:

$$y_{it} = \left(\left(\mathbf{p}_{it} \otimes \mathbf{z}_{it} \right) \otimes \mathbf{x}_t \right) \beta + v_{it} \tag{12}$$

where vector β comprises the regression coefficients and the explanatory variables are obtained as the Kronecker product ($\otimes$) of vectors $\mathbf{p}_{it}$, $\mathbf{z}_{it}$, and $\mathbf{x}_t$.

Vector $\mathbf{x}_t$ determines how the risk-adjusted performance of the sample firms is measured. We rely on the three Fama-French (1993) factors (market, size, and book-to-market factors) and Carhart's (1997) momentum factor. Correspondingly, we specify vector $\mathbf{x}_t$ as

$$\mathbf{x}_t = \left[\begin{array}{ccccc} 1 & \mathrm{RMRF}_t & \mathrm{SMB}_t & \mathrm{HML}_t & \mathrm{MOM}_t \end{array} \right] \tag{13}$$

where RMRF_t denotes the market factor, SMB_t is the return of a zero-investment size portfolio, HML_t refers to the return of a zero-investment book-to-market portfolio, and MOM_t is the return of a zero-investment momentum portfolio.[24] In contrast to the risk factors contained in vector $\mathbf{x}_t$ which vary over time but not across firms, the firm characteristics in vectors $\mathbf{p}_{it}$ and $\mathbf{z}_{it}$ are allowed to vary across both the time dimension and the cross-section. While we change in the regressions the composition of vector

$$\mathbf{z}_{it} = \begin{bmatrix} 1 & z_{1,it} & \cdots & z_{M,it} \end{bmatrix} \tag{14}$$

which includes a constant and a set of M firm characteristics $z_{m,it}$ ($m = 1, ..., M$), we do not vary the configuration of vector $\mathbf{p}_{it}$. The latter vector always includes a constant and a dummy variable (D_{it}^{τ}) that is 1 if a firm's IPO occurred within the last τ years and zero otherwise, i.e.

$$\mathbf{p}_{it} = \begin{bmatrix} 1 & \mathrm{D}_{it}^{\tau} \end{bmatrix} \tag{15}$$

5.2 Over what horizon do IPO firms underperform?

We start by examining whether the stocks of firms going public really underperform those of more mature companies and, if so, over what horizon the underperformance is statistically significant. To our best knowledge, there is no prior study investigating explicitly the time horizon over which IPO firms underperform. According to Kothari and Warner (2007) the definition of a "long horizon" in event studies is arbitrary and generally applies to event windows of one year or more. Hence, instead of simply relying on the standard length of five years used in prior research (e.g., Brav and Gompers, 1997; Brav, Geczy, and Gompers, 2000), we consider five different definitions for the IPO dummy D_{it}^{τ}. Namely, we set τ equal to one, two, three, four, and five years, respectively.

In order to test for IPO underperformance, we do not have to include in the analysis any firm characteristics other than the IPO dummy D_{it}^{τ}. Consequently, we define vector $\mathbf{z}_{it}$ as $\mathbf{z}_{it} = [1]$.

[24] We use the value-weighted average return of all NYSE, AMEX and NASDAQ stocks contained in the CRSP database as a proxy for the return of the market portfolio and obtain the risk free return from Ibbotson Associates. Data on the size, value, and momentum factors stem from Kenneth French's website: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library`.

Inserting vectors $\mathbf{p}_{it}$, $\mathbf{z}_{it}$, and $\mathbf{x}_t$ into the GCT-regression model (12), we obtain the following regression specification:

$$\begin{aligned} y_{it} = \quad & \beta_0 & & + \beta_5 \times \mathrm{D}_{it}^{\tau} \\ & + \beta_1 \times \mathrm{RMRF}_t & & + \beta_6 \times (\mathrm{D}_{it}^{\tau} \times \mathrm{RMRF}_t) \\ & + \beta_2 \times \mathrm{SMB}_t & & + \beta_7 \times (\mathrm{D}_{it}^{\tau} \times \mathrm{SMB}_t) \\ & + \beta_3 \times \mathrm{HML}_t & & + \beta_8 \times (\mathrm{D}_{it}^{\tau} \times \mathrm{HML}_t) \\ & + \beta_4 \times \mathrm{MOM}_t & & + \beta_9 \times (\mathrm{D}_{it}^{\tau} \times \mathrm{MOM}_t) + v_{it} \end{aligned} \tag{16}$$

Table IV presents the results from estimating regression (16) with Driscoll and Kraay (1998) standard errors. For all five definitions of D_{it}^{τ} ($\tau = 1, ..., 5$), the structure of the tabulated results exactly matches the outline of equation (16). Accordingly, the estimation results are partitioned into two columns: Columns labeled with "OLD" contain the coefficient estimates and t-statistics (in parentheses) for the mature companies. Specifically, these results include the mature firms' risk-adjusted performance ($\hat{\beta}_0$) and their factor risk exposures ($\hat{\beta}_1$ through $\hat{\beta}_4$). In contrast, columns labeled with "Δ(IPO-OLD)" present the results for the interaction terms between the risk factors (or the regression constant) and the IPO dummy. The corresponding regression coefficients indicate by how much the risk-adjusted performance ($\hat{\beta}_5$) and the factor risk exposures ($\hat{\beta}_6$ through $\hat{\beta}_9$) of IPO firms differ from those of more mature companies.

When estimating regression (16), we are primarily interested in the coefficient estimate for the IPO dummy ($\hat{\beta}_5$). If it is negative and significantly different from zero, this indicates that the risk-adjusted performance of IPO firms is worse than that of more mature companies. The empirical results presented in Table IV indicate that while the coefficient estimate for D_{it}^{τ} is negative for all five IPO definitions, it is significant only if IPO firms are defined as firms going public within the last year or the last two years, respectively. In contrast, by referring to IPO firms as companies whose initial public offering occurred within the last three, four, or five years, the coefficient estimate for the IPO dummy becomes insignificant. Moreover, the results in Table IV show that the "Beta" of IPO firms is significantly higher than that of more mature companies and that IPO firms have a significantly smaller exposure to the HML_t factor than older companies. These results hold for all IPO definitions considered in the table.[25]

In order to provide a more complete picture of the relation between time horizon and IPO performance, Figure 3 additionally displays the evolution of the coefficient estimate for the IPO dummy when regression (16) is estimated with IPO firm definitions ranging from "firms going public within the last quarter" to "firms going public within the last 10 years". Most importantly, the figure reveals that IPO underperformance is strongest after one year and then gradually decreases over the subsequent years corroborating the results from Table IV. To summarize, we can answer the initial question of whether the stocks of IPO firms underperform those of more mature companies with "yes". However, our results indicate that IPO underperformance is most pronounced during the first two years after the IPO.

5.3 Why do IPOs underperform?

In order to investigate more thoroughly *why* IPOs underperform, we include in the GCT-regression (12) a series of firm characteristics as explanatory variables. We do so by augmenting vector $\mathbf{z}_{it}$ with variables that are related to the IPO market environment, leverage and liquidity, firm valuation, corporate diversification strategies, and investments. While we adhere to the definition of vector $\mathbf{x}_t$ in (13), all GCT-regressions estimated in this section rely on vector $\mathbf{p}_{it}$ being set to $\mathbf{p}_{it} = [\ 1 \quad \mathrm{D}_{it}^1\ ]$, where D_{it}^1 is a dummy variable with value one if the IPO of firm i took place within the last year and zero otherwise. The reason for specifying $\mathbf{p}_{it}$ like this is due to the evidence reported in Section 5.2 according to which IPO underperformance is most significant in the first year after going public. It is important to accentuate that our paper differs in this respect from prior research (e.g., Brav and Gompers, 1997; Brav, Geczy, and Gompers, 2000) where IPO firms are typically defined as companies going public within the last five years.

We present the results for the regressions considered in this section in Tables V and VI.

[25] A potential concern in Table IV is that firms going public within the last 5 years are treated as "mature" firms if their IPO occurred more than τ years ago. However, the results remain unchanged if we exclude from the regressions all non-mature firms (i.e., younger than 5 years) with $\mathrm{D}_{it}^{\tau} = 0$ ($\tau = 1, ..., 5$).

While the coefficient estimates and t-statistics (in parentheses) for the firm characteristics in vector $\mathbf{z}_{it}$ are reported in columns labeled with 'OLD', the estimation results for the interaction terms between the firm characteristics and the IPO dummy (D^1_{it}) are displayed in columns labeled with 'Δ(IPO-OLD)'. For brevity, however, we do not tabulate the results for the four risk factors (RMRF_t, SMB_t, HML_t, and MOM_t) and their interaction terms. If a set of firm characteristics is capable to 'explain' IPO underperformance, the coefficient estimate for the IPO dummy, which is reported in the first row of columns labeled with 'Δ(IPO-OLD)', should be insignificant.

We start by examining whether IPO underperformance is a consequence of the issue period. In doing so, we specify vector $\mathbf{z}_{it}$ as $\mathbf{z}_{it} = [\ 1 \quad \mathrm{HOT}_i \quad \mathrm{COLD}_i\ ]$ where HOT_i and COLD_i are dummy variables set to one for firms going public in hot and cold markets, respectively. From the estimation results reported in regression 'Issue Period' of Table V it is apparent that neither the coefficient estimate for the $\mathrm{HOT} \times \mathrm{IPO}$ interaction nor that for the $\mathrm{COLD} \times \mathrm{IPO}$ interaction is statistically significant. By contrast, the coefficient estimate for the IPO dummy remains negative and significant at the 5% level. As a result, it follows that accounting for hot and cold issue markets does not explain IPO underperformance.

We proceed by relying upon the evidence in Eckbo and Norli (2005). Correspondingly, we specify vector $\mathbf{z}_{it}$ as $\mathbf{z}_{it} = [\ 1 \quad \mathrm{Leverage}_{i,t-1} \quad \mathrm{ATurn}_{i,t-1}\ ]$, where $\mathrm{Leverage}_{i,t-1}$ refers to the firms' market leverage by end of quarter $t-1$ and $\mathrm{ATurn}_{i,t-1}$ measures the firms' abnormal turnover during quarter $t-1$. The results in Column 'Δ(IPO-OLD)' from regression 'Leverage & Liquidity' reveal that neither Leverage nor (abnormal) trading volume are able to explain IPO underperformance. As such, the coefficient estimate for the IPO dummy remains negative and statistically significant at the 5% level. In addition, both the coefficient estimates for the $\mathrm{Leverage} \times \mathrm{IPO}$ and the $\mathrm{ATurn} \times \mathrm{IPO}$ interactions are insignificant. Consequently, the impact of leverage and abnormal trading volume on future stock excess returns is no different for IPO companies as compared to non-issuing (mature) firms.

As a next step, we include in vector $\mathbf{z}_{it}$ the firms' industry-adjusted excess valuation measure (XVAL) by end of quarter $t-1$ and, correspondingly, specify $\mathbf{z}_{it} = [\ 1 \quad \mathrm{XVAL}_{i,t-1}\ ]$.

The estimation results for regression 'Excess Valuation' indicate, that on a risk-adjusted basis, mature firms with a high (excess) valuation tend to perform significantly worse than low-valued companies. Interestingly, the coefficient estimate for the XVAL variable turns out to be highly significant even though we already account for the firms' valuation and incorporated growth expectations by including the return of a zero-investment book-to-market portfolio (HML factor) in the regression. As a result, our simple measure of the firms' excess valuation has additional explanatory power for the cross-section of stock returns which is not captured by the HML factor. Moreover, the coefficient estimate for the $\mathrm{XVAL} \times \mathrm{IPO}$ interaction is positive and marginally significant at the 10% level. Since the coefficient estimate for the interaction term is smaller (on an absolute scale) than that for the non-interacted XVAL variable, the underperformance associated with a high excess value is less severe for IPO firms than for mature companies. Put differently, valuation is less critical for future stock returns of IPO firms as compared to more seasoned companies. However, because the coefficient estimate for the IPO dummy remains negative and significant at the 5% level, we conclude that our XVAL measure alone cannot explain IPO underperformance either.

Next, we aim at investigating whether IPO underperformance is related to corporate diversification strategies. In doing so, we specify vector $\mathbf{z}_{it}$ as $\mathbf{z}_{it} = [\ 1 \quad \mathrm{Diversified}_{i,t-1}\ ]$ where $\mathrm{Diversified}_{i,t-1}$ is a dummy variable with value one for firms reporting multiple segments in COMPUSTAT's annual Segments data file.[26] The estimation results for regression 'Diversification' in Table V are consistent with prior studies as they reveal that diversified companies significantly underperform focused firms. In addition, the negative and marginally significant coefficient estimate for the $\mathrm{Diversified} \times \mathrm{IPO}$ interaction indicates that the impairment of performance associated with corporate diversification strategies is even stronger for IPO firms than for more mature companies. However, corporate diversification strategies cannot fully explain IPO underperformance. As before, the coefficient estimate for the IPO dummy turns out to be negative and significant at the 5% level.

[26]Note that the Diversified dummy is assumed to be constant during all quarters of a calendar year. Therefore, it holds true that $\mathrm{Diversified}_{i,t-1} = \mathrm{Diversified}_{i,t}$ unless t falls on the first quarter of a year. As a result and in contrast to the other regression specifications considered so far, this regression does not constitute a true look-ahead regression with respect to the Diversified dummy.

Since none of the above GCT-regressions was able to explain IPO underperformance, we proceed by examining whether the entire set of firm characteristics considered so far can explain IPO underperformance. Consequently, we specify vector $\mathbf{z}_{it}$ as

$$\mathbf{z}_{it} = [\ 1 \quad \mathrm{HOT}_i \quad \mathrm{COLD}_i \quad \mathrm{Leverage}_{i,t-1} \quad \mathrm{ATurn}_{i,t-1} \quad \mathrm{XVAL}_{i,t-1} \quad \mathrm{Diversified}_{i,t-1}\ ] \,.$$

The results from estimating this GCT-regression are presented in Table V, columns labeled with 'All (except expenditures)'. Even for this extended model the coefficient estimate for the IPO dummy turns out to be negative and (marginally) significant. Consequently, IPO underperformance persists even after controlling for the issue period, leverage, liquidity, valuation, and the firms' corporate diversification strategies. Specifically, the estimation results reveal that by controlling for all these firm characteristics, the average risk-adjusted underperformance of IPO firms compared to more mature companies amounts to a sizable and marginally significant 2.633% per quarter.

According to Kim and Weisbach (2007), an important motive for going public is to raise capital for investments. Specifically, they show that during the first year after going public, the average IPO firm invests 18.5 cents in R&D expenditures and 9.9 cents in capital expenditures for each incremental dollar raised in the IPO. These numbers rise to 78.0 cents and 19.9 cents, respectively, when the change is measured over a four-year period. Consequently, we follow our course of action in the multivariate BHAR-analysis of Section 4.4 and pursue by investigating whether the firms' investments might be the reason for IPO underperformance. We therefore set vector $\mathbf{z}_{it}$ to $\mathbf{z}_{it} = [\ 1 \quad \mathrm{CAPEX}_{i,t-1} \quad \mathrm{Acquisitions}_{i,t-1} \quad \mathrm{R\&D}_{i,t-1} \quad \mathrm{missR\&D}_{i,t-1}\ ]$, where $\mathrm{CAPEX}_{i,t-1}$ refers to firm i's capital expenditures during quarter $t-1$ scaled by sales, $\mathrm{Acquisitions}_{i,t-1}$ denotes the firms's quarterly acquisitions-to-sales ratio, $\mathrm{R\&D}_{i,t-1}$ summarizes the firms' quarterly R&D-to-sales ratio where missing values are replaced by zero, and $\mathrm{missR\&D}_{i,t-1}$ is a dummy variable being one if no R&D expenditures are available from COMPUSTAT and zero otherwise.[27]

[27] For details on why to replace missing R&D-to-sales ratios with zero, please see Section 4.4 and particularly footnote 23.

We present the estimation results for this regression in Columns 1 and 2 ('Expenditures') of Table VI. The results reveal that firms with high capital expenditures, companies engaging in large acquisitions, and firms disclosing no R&D figures perform significantly worse over the subsequent quarter. However, the insignificant coefficient estimates for the $\mathrm{CAPEX} \times \mathrm{IPO}$ and $\mathrm{Acquisitions} \times \mathrm{IPO}$ interactions indicate that with respect to these dimensions, IPO firms are no different from more mature companies. By contrast, the positive and significant coefficient estimate for the $\mathrm{missR\&D} \times \mathrm{IPO}$ interaction reveals that IPO firms not disclosing R&D figures tend to slightly outperform those which publish their R&D expenditures (the coefficient estimate for the interaction term is larger in absolute terms than that for the $\mathrm{missR\&D}$ dummy). But once again, the coefficient estimate for the IPO dummy turns out to be negative and highly significant. Consequently, we conclude that the four investment-related variables considered in this regression cannot explain IPO underperformance.

For our final regression, we include in vector $\mathbf{z}_{it}$ all the firm characteristics considered in this Section. The results from estimating this 'Full sample (1975-2005)' regression are presented in Table VI. Most importantly, the coefficient estimate for the IPO dummy variable finally becomes insignificant. Hence, by controlling for a sufficient number of firm characteristics, we can 'explain' why IPO firms underperform. While most of the coefficient estimates for the interaction terms are insignificant, those for the $\mathrm{missR\&D} \times \mathrm{IPO}$, $\mathrm{COLD} \times \mathrm{IPO}$, and $\mathrm{XVAL} \times \mathrm{IPO}$ interactions are positive and (marginally) significant. Correspondingly, if the performance of IPO firms indeed differs from that of the more seasoned companies, then the difference is in favor of the IPO firms. Specifically, the estimation results indicate that (excess) valuation plays a somewhat less important role for IPO companies than for mature firms, IPO firms not reporting their R&D expenditures do not underperform as compared to (mature) firms that publish their R&D expenditures, and firms going public in cold issue markets outperform the more seasoned companies (after controlling for all the other characteristics). Consistent with our findings from the descriptive analysis in Section 3, we therefore conclude that the documented IPO underperformance is mainly the result of the IPO companies' firm characteristics being fundamentally different from those of the more seasoned companies. However, when over time the characteristics of IPO firms converge to those of more seasoned companies, the same holds true for the stock returns and the IPO underperformance vanishes. Consequently, we would be careful with speaking of an 'IPO underperformance anomaly'. Moreover, our results are in line with the findings of, among others, Brav and Gompers (1997) and Brav, Geczy, and Gompers (2000) who present evidence that the low post-issue returns of IPOs are consistent with the Fama and French (1993) three-factor model as IPO firms are predominantly small growth firms. However, in contrast to these studies, for our more recent IPO sample and our alternative definition of IPO firms the three Fama-French factors and Carhart's (1997) momentum factor are not able to fully explain IPO underperformance.[28] We need to control for a comprehensive set of additional firm characteristics.

In order to test whether the results from the 'Full sample (1975-2005)' regression are robust to changes in the sample period and sample selection, we reestimate the regression for three sub-samples. We obtain our first sub-sample by restricting our sample data to the set of observations with a verified link between the CRSP and COMPUSTAT databases. Second, we constrain the sample data to the 1975-1998 period which is close to the period covered by Eckbo and Norli (2005).[29] The importance of the sample period for the estimation results is emphasized by, among others, Ritter and Welch (2002, p. 1820) who argue that "one must be careful comparing papers which attribute a weakening or disappearance of the IPO effect to novel measurement techniques; instead, the sample period may be responsible for some of the conclusions." As such, it might well be that the hot issue markets of the late 1990s and the subsequent cold issue period substantially affect our results. Third and finally, we once more bear in mind the study of Eckbo and Norli (2005) and restrict our sample data to the subset of firms that are traded on the Nasdaq stock exchange.

We present the estimation results for the sub-sample regressions in Table VI. From the

[28] As explained at the beginning of this section and based on the evidence in Section 5.2, we define IPO firms as companies going public within the last 12 months. In contrast, Brav and Gompers (1997) and Brav, Geczy, and Gompers (2000) define IPO firms as companies going public within the last five years.

[29] Eckbo and Norli (2005) analyze a dataset on Nasdaq IPOs that relies on data for the 1972-1998 period. Unfortunately, however, the three years from 1972 through 1974 are not covered in the Field-Ritter dataset of company founding dates upon which we base our analysis. Alternatively, we re-estimate the regression for the 1975-1992 period corresponding to the sample period covered by Brav, Geczy, and Gompers (2000) and find similar results.

estimation results presented in columns labeled with ‘Valid link’, ‘Period: 1975-1998’, and ‘NASDAQ firms only’, respectively, it follows that the coefficient estimate for the IPO dummy variable is negative but insignificant in all three sub-sample regressions. This asserts that the firm characteristics considered in our analysis are indeed able to ‘explain’ IPO underperformance. Moreover, even though our sub-sample regressions are based on much fewer observations than the ‘Full sample (1975-2005)’ regression, the signs of the coefficient estimates (and even their significance) are remarkably stable.

As a final check on the robustness of our results, we investigate whether the firm characteristics considered in this section are simply a proxy for firm age. We proceed in two steps: First, we regress firm age on all explanatory variables included in Columns 3 and 4 (‘Full sample (1975 - 2005)’) of Table VI. Second, we then estimate the GCT-regression (12) with vector $\mathbf{z}_{it}$ being specified as $\mathbf{z}_{it} = [\ 1 \quad \hat{\mathrm{Age}}_{i,t-1}\ ]$, where $\hat{\mathrm{Age}}_{i,t-1}$ refers to the predicted values of firm age derived from the first-step regression. In unreported results, we find the coefficient on $\hat{\mathrm{Age}}$ to be negative and significant while the coefficient estimate for the $\hat{\mathrm{Age}} \times \mathrm{IPO}$ interaction is positive and insignificant.[30] Most importantly, however, the coefficient estimate for the IPO dummy remains negative and statistically significant. From this it follows that the firm characteristics considered in the analysis do provide additional information and thus are not just a proxy for firm age.

6 Conclusion

We address three different questions related to the long-term performance of IPO firms. First, we investigate whether IPO performance is to a certain extent predictable based on a set of firm characteristics which are known by the time of the IPO. Second, we focus on the time horizon over which IPOs underperform and, third, we investigate why IPOs underperform.

It is well-known that measuring the long-term performance is ‘treacherous’ (Lyon, Bar-

[30] The results are available form the authors upon request.

ber, and Tsai, 1999) and, hence, that the methodology for assessing the long-term performance plays a crucial role for the validity of the results. In this paper, we rely on two estimation methods. Both of them allow for the inclusion of (multivariate) firm-characteristics as explanatory variables and assure that statistical inference is heteroscedasticity consistent and robust to cross-sectional and temporal dependence.

In order to investigate *which* firm characteristics possess explanatory power for the subsequent performance of IPO stocks, we introduce a regression-based generalization of Jegadeesh and Karceski's (2004) robust version of the BHAR-approach. The key finding of this analysis is that IPOs associated with overly optimistic growth prospects (and correspondingly high valuation levels) perform worse than IPOs for which growth expectations are more modest. As pointed out by Loughran and Ritter (1995), the extraordinary growth rates of some recent IPOs can justify excessive valuation levels if investors believe that they have identified the next Microsoft. However, our empirical results reveal that such investors betting on "longshots" do substantially worse than investors focusing on IPOs with more moderate valuation levels as the probability of investing in a reasonably well-performing IPO firm is disproportionally higher in the latter case. Hence, investors seem to be systematically overoptimistic in assessing the probability of identifying the next Microsoft and, as a consequence, the respective candidate IPOs are valued too high.

In order to examine the time horizon over which IPO firms underperform and to investigate the reasons for the underperformance, we rely on Hoechle and Zimmermann's (2007) GCT-regression model. While prior research generally defines IPO firms as companies going public within the last five years, we explicitly investigate the time horizon over which IPO firms underperform. The main result of this analysis is that IPO underperformance is most pronounced during the first year after the IPO. As a consequence, when analyzing the reasons for IPO underpformance we define IPO firms as companies going public within the last twelve months.

The results of our GCT-analysis reveal that there is no single firm characteristic which explains why the stocks of IPO firms tend to underperform in the first year after the going public. However, by including in the GCT-regression a comprehensive set of explanatory variables related to the IPO market environment, leverage and liquidity, firm valuation, corporate diversification strategies, and investment expenditures, we can 'explain' IPO underperformance. This finding strongly underscores the advantage of the GCT-regression approach: By allowing for the inclusion of continuous and multivariate firm characteristics in the analysis, the GCT-regression model constitutes a convenient way to overcome the one-dimensionality of the traditional calendar time portfolio approach used in prior research. We conclude that the documented IPO underperformance is mainly the result of fundamental differences in firm characteristics between IPO and more seasoned (non-issuing) firms. Put differently, IPO firms do not perform materially better or worse than mature companies with similar firm characteristics.

As a result, even though the returns of IPO stocks *are* lower than those for the more seasoned companies, we do not find evidence for an 'IPO underperformance anomaly'. In the context of the BHAR approach, IPO underperformance is likely to be the consequence of imperfect (i.e., too few dimensional) matching procedures and in the context of the traditional calendar time portfolio approach the documented IPO underperformance (if any) is likely to be the result of the Fama-French (1993) or Carhart (1997) factors not being able to fully explain variations in the cross-section of stock returns.

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Appendix A Proof of Proposition 1

By stacking the N_t abnormal returns in month t into vector $\mathbf{A}'_t = [\ AR_{1t} \quad \cdots \quad AR_{N_t t}\ ]$, we obtain the following coefficient estimate for the intercept term α:

$$\hat{\alpha} = \left(\iota'\iota\right)^{-1} \iota'\mathbf{A}_{it} = N^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N_t} AR_{it} = \sum_{t=1}^{T}\frac{N_t}{N} \times AR_t = \sum_{t=1}^{T} w_t \times AR_t = \overline{AR} \qquad \text{(A-1)}$$

where $\mathbf{A}'_{it} = [\ \mathbf{A}'_1 \quad \cdots \quad \mathbf{A}'_T\ ]$ and ι is a $N \times 1$ vector of ones.

To derive the Driscoll and Kraay (1998) standard error of $\hat{\alpha}$, we start with the special case of the Driscoll-Kraay estimator for an intercept-only pooled OLS regression. It is given by

$$V\left\{\hat{\alpha}\right\} = N^{-2}\left(\hat{\Omega}_0 + \sum_{j=1}^{H-1}\omega_{j,H}\left(\hat{\Omega}_j + \hat{\Omega}'_j\right)\right) \qquad \text{(A-2)}$$

$$\text{with} \quad \hat{\Omega}_j = \sum_{q=j+1}^{T} N_q N_{q-j}\left(AR_q - \overline{AR}\right)\left(AR_{q-j} - \overline{AR}\right)$$

Replacing $\hat{\Omega}_0$ and $\hat{\Omega}_j$ in the first row of (A-2) by the term of the second row and using $w_t = N_t/N$, we finally obtain the Driscoll-Kraay estimator for $\hat{\alpha}$ as

$$\begin{aligned} V\left\{\hat{\alpha}\right\} &= \sum_{t=1}^{T} w_t^2\left(AR_t - \overline{AR}\right)^2 \\ &\quad + 2\sum_{j=1}^{H-1}\omega_{j,H}\sum_{q=j+1}^{T} w_q w_{q-j}\left(AR_q - \overline{AR}\right)\left(AR_{q-j} - \overline{AR}\right) \qquad \text{(A-3)} \end{aligned}$$

Now, we turn to the centered version of Jegadeesh and Karceski's (2004) estimator for the variance of the average H-month buy-and-hold abnormal return. Using $ar_j \equiv \left(AR_j - \overline{AR}\right)$, we can write out covariance matrix $\mathbf{\Omega}$ with kj^{th} element $\hat{\phi}^c_{kj}$ being estimated according to expression (8) as

$$
\mathbf{\Omega} = \begin{bmatrix}
ar_1^2 & ar_1\, ar_2 & \cdots & ar_1\, ar_{H-1} & 0 & 0 & \cdots & 0 \\
ar_1\, ar_2 & ar_2^2 & \cdots & ar_2\, ar_{H-1} & ar_2\, ar_H & 0 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & & \ddots & \vdots \\
ar_1\, ar_{H-1} & ar_2\, ar_{H-1} & \cdots & ar_{H-1}^2 & ar_{H-1}\, ar_H & & & 0 \\
0 & ar_2\, ar_H & \cdots & ar_{H-1}\, ar_H & ar_H^2 & & & \\
0 & 0 & & & & \ddots & & \\
\vdots & \vdots & \ddots & & & & \ddots & \\
0 & 0 & \cdots & 0 & & & & ar_T^2
\end{bmatrix} \tag{A-4}
$$

Thus, by relying on $\mathbf{\Omega}$ in (A-4) we finally obtain the Jegadeesh-Karceski variance for the H-month BHAR, $V\{\overline{AR}\} = \mathbf{w}'\mathbf{\Omega}\mathbf{w}$, as

$$
\begin{aligned}
V\left\{\overline{AR}\right\} \;&=\; \sum\nolimits_{t=1}^{T} w_t^2 \left(AR_t - \overline{AR}\right)^2 \\
&\quad + \; 2\sum\nolimits_{j=1}^{H-1} \sum\nolimits_{q=j+1}^{T} w_q w_{q-j} \left(AR_q - \overline{AR}\right)\left(AR_{q-j} - \overline{AR}\right)
\end{aligned} \tag{A-5}
$$

Expression (A-5) is identical to that for $V\left\{\hat{\alpha}\right\}$ in (A-3) with rectangular weights $\omega_j^H = 1$ ($j = 1, ..., H-1$) for the lags. As a result, the centered version of JK's HSC_t statistic coincides with the Driscoll-Kraay t-statistic for $\hat{\alpha}$ from estimating the intercept only regression in (9). ■

Table I

Descriptive statistics

The table summarizes firm characteristics for 7,378 companies going public between 1975 and 2005, and their non-issuing control firms matched on size and book-to-market ratio. All figures represent characteristics for the (or by end of the) quarter in which the IPO takes place. Figures on size, book value of equity, and sales are in millions of 2005 USD. Hot issue periods are quarters with more than 101 IPOs, cold issue quarters count less than 43 IPOs, and neutral issue periods are quarters with at least 43 and at most 101 IPOs.

		Size matching		Size and book-to-market matching				Characteristics of IPO firms by issue period		
		Issuer	Match	Issuer	Match	Issuer (valid link)	Match (valid Link)	Hot	Neutral	Cold
# of firms		7,378	7,378	6,257	6,257	3,970	3,970	4,206	1,966	1,206
Size (market capitalization)	mean	399.96	401.40	429.10	416.97	440.04	424.79	436.68	319.52	403.00
	median	121.27	121.45	132.37	128.86	142.91	136.77	131.83	102.69	116.38
Book value of equity	mean	133.29	212.34	128.20	120.62	106.79	120.98	109.78	103.42	293.27
	median	40.15	77.78	40.26	38.56	40.64	41.77	40.15	35.62	48.97
Market-to-Book ratio	mean	3.545	1.845	3.544	3.215	3.635	3.173	3.814	3.271	2.898
	median	2.494	1.270	2.495	2.452	2.559	2.468	2.614	2.353	2.206
Sales	mean	73.14	153.45	73.65	72.08	62.69	63.05	57.52	69.77	144.16
	median	13.24	47.60	13.40	18.80	12.13	16.92	11.89	13.95	18.18
Book leverage	mean	0.366	0.510	0.365	0.417	0.351	0.394	0.349	0.387	0.404
	median	0.311	0.524	0.309	0.394	0.291	0.366	0.291	0.342	0.366
Market leverage	mean	0.195	0.414	0.195	0.225	0.185	0.207	0.179	0.214	0.231
	median	0.121	0.398	0.120	0.160	0.108	0.146	0.102	0.131	0.167
CAPEX per sales	mean	0.311	0.195	0.311	0.229	0.325	0.250	0.335	0.273	0.281
	median	0.103	0.076	0.103	0.087	0.109	0.091	0.112	0.090	0.089
R&D per sales	mean	0.379	0.173	0.377	0.294	0.401	0.336	0.379	0.409	0.322
	median	0.121	0.057	0.121	0.088	0.131	0.098	0.130	0.106	0.101
Acquisitions per sales	mean	0.136	0.066	0.137	0.048	0.117	0.054	0.165	0.107	0.067
	median	0	0	0	0	0	0	0	0	0

Table II

5-year BHARs for IPO and matched firms

The table reports five-year (forward written) buy-and-hold abnormal returns (BHARs) for 6,828 firms going public between 1975 and 2000. The matching algorithm either relies on firm size (Panel A), size and the book-to-market ratio (Panel B), or size and the book-to-market ratio with a verified link between the CRSP database and COMPUSTAT (Panel C). BHARs exceeding 1500% in absolute value are excluded from the analysis. The definitions of the t-statistics for the BHARs are as follows: The "conventional" t-statistic is computed according to equation (**4**) of the paper. The "JK uncentered" t-statistic refers to Jegadeesh and Karceski's (2004) *HSC_t* statistic and the "JK centered" t-statistic is the centered version of the *HSC_t* statistic as defined in equation (**8**) of the paper. Finally, the "DK" t-statistic is obtained from estimating the intercept only regression (**9**) with Driscoll and Kraay (1998) standard errors. Low-valued IPOs have $-1.386 \leq \text{XVAL} \leq 0$, where XVAL refers to an industry-adjusted excess valuation measure that is based on the firms' sales in the IPO quarter. High-valued IPOs have $0 < \text{XVAL} \leq 1.386$. IPOs with $abs(\text{XVAL}) > 1.386$ are recoded to have a missing excess value measure. Of the 2,880 firms with XVAL being classified as missing, 1,574 in fact possess an excess value measure which is bigger in absolute terms than 1.386. In order to assess whether or not the difference between the BHAR of low-valued and the BHAR of high-valued IPOs is significantly different from zero, we estimate the following regression and base our statistical inference on the significance for the coefficient estimate of β:

$$AR_{it} = \alpha + \beta D_{low,i} + \varepsilon$$

where $D_{low,i}$ is a dummy variable being one for IPOs with $-1.386 < \text{XVAL} <= 0$, zero for IPOs with $0 < \text{XVAL} < 1.386$, and missing otherwise. ***, **, * indicate significance at the 1, 5, and 10 percent level.

		All IPOs	low-valued IPOs	high-valued IPOs	IPOs with missing XVAL	Low- minus high-valued IPOs
Panel A: Size matching						
# IPO firms with non-missing 5y BHAR		6,828	1,237	2,711	2,880	3,948
avg. 5y BHAR		-34.993	-5.677	-24.465	-57.494	18.788
t-statistic	conventional	-12.653***	-0.926	-5.514***	-13.445***	2.420**
	JK uncentred	-3.348***	-0.845	-3.035***	-3.203***	2.288**
	JK centred	-4.832***	-0.846	-4.009***	-5.975***	2.640**
	DK	-6.197***	-0.895	-4.655***	-7.463***	2.730**
Median XVAL	IPO firms	0.647	-0.334	0.596	2.253	-0.930
	matching firms	-0.005	-0.021	-0.000	-0.006	-0.021
Panel B: B/M and size matching						
# IPO firms with non-missing 5y BHAR		5,737	1,227	2,694	1,816	3,921
avg. 5y BHAR		-10.315	7.769	-6.220	-28.608	13.989
t-statistic	conventional	-3.505***	1.233	-1.397	-5.797***	1.782*
	JK uncentred	-1.902*	1.130	-1.276	-2.350**	1.638
	JK centred	-2.114**	1.176	-1.329	-3.414***	1.731*
	DK	-2.538**	1.262	-1.416	-4.043***	1.913*
Median XVAL	IPO firms	0.647	-0.333	0.596	2.253	-0.929
	matching firms	0.302	0.000	0.252	0.715	-0.252
Panel C: B/M and size matching with verified link between CRSP and COMPUSTAT						
# IPO firms with non-missing 5y BHAR		3,559	707	1,658	1,194	2,365
avg. 5y BHAR		-21.387	-10.074	-13.573	-38.937	3.499
t-statistic	conventional	-6.145***	-1.402	-2.584***	-6.492***	0.376
	JK uncentred	-3.190***	-1.557	-2.123**	-2.904***	0.411
	JK centred	-4.812***	-1.688	-2.486**	-4.957***	0.414
	DK	-5.555***	-1.640	-2.640***	-5.483***	0.445
Median XVAL	IPO firms	0.704	-0.348	0.599	2.285	-0.947
	matching firms	0.310	0.000	0.224	0.737	-0.224

Table III

Multivariate BHAR analysis: Firm characteristics and IPO performance

This table reports the coefficient estimates and t-values (in parentheses) from OLS regressions with Driscoll-Kraay standard errors. The standard error estimates are heteroscedasticity consistent and robust to both cross-sectional dependence and autocorrelation up to 60 lags, respectively. The dependent variable in all regressions is the IPO firms' 5-year buy-and-hold abnormal return (BHAR) compared to a size-matched non-issuing company. The explanatory variables are an industry-adjusted excess valuation measure based on the IPO firms' sales during the quarter in which the IPO took place (XVAL), a dummy variable being 1 for all IPO firms going public in a quarter with more than 101 IPOs (HOT), a dummy with value one for all IPO firms whose initial public offering occurred in a quarter with less than 43 IPOs (COLD), the market leverage ratio by the end of the firms' IPO quarter (Leverage), a dummy variable being one if an IPO firm's business segments in the calendar year of the IPO are located in two or more industries based on the NAICS code (Diversified), the IPO firms' capital expenditures in the IPO quarter scaled by sales (CAPEX), the firms' acquisitions during the IPO quarter scaled by sales (Acquisitions), and the IPO firms' R&D expenditures in the IPO quarter scaled by sales (R&D). Since R&D is often missing, we replace missing values for R&D by 0 but include a dummy variable which equals 1 if R&D is missing in the regressions (missR&D). The sample data comprises 6,828 firms going public in the period 1975 through 2000. ***, **, * indicate significance at the 1, 5, and 10 percent level.

	Excess Valuation	Issue Period	Leverage	Diversification	All (except expenditures)	Expenditures	All
Constant	-15.126***	-29.585***	-49.199***	-35.668***	-6.787	-35.810***	-9.760
	(-2.619)	(-3.244)	(-4.508)	(-3.061)	(-0.669)	(-3.161)	(-1.243)
XVAL	-17.504***				-16.898***		-18.041***
	(-7.369)				(-5.553)		(-4.376)
HOT		-4.891			-18.960***		-14.682***
		(-0.640)			(-3.321)		(-3.128)
COLD		-19.436			-17.161		-17.335
		(-1.261)			(-1.332)		(-1.450)
Leverage			89.020***		28.966		-3.780
			(4.715)		(1.636)		(-0.161)
Diversified				11.791	9.224		6.649
				(1.113)	(1.221)		(0.799)
CAPEX						-21.484***	-5.070**
						(-4.636)	(-1.972)
Acquisitions						-2.086	-5.320
						(-0.626)	(-1.529)
R&D						0.980	7.628
						(0.137)	(1.165)
missR&D						26.058**	24.434*
						(2.382)	(1.930)
# obs.	5,522	6,828	5,731	4,409	3,612	4,746	3,059
R^2	0.0118	0.0006	0.0061	0.0003	0.0150	0.0063	0.0146

Table IV

Is IPO underperformance related to firm age since IPO?

This table reports the coefficient estimates and t-values (in parentheses) of pooled OLS regressions with Driscoll-Kraay standard errors. The standard error estimates are heteroscedasticity consistent and robust to both cross-sectional dependence and autocorrelation up to four lags, respectively. In all regressions the firms' quarterly excess return (incl. distributions) over the next quarter is the dependent variable. The sample data comprises an unbalanced panel of 7,378 firms going public between 1975 and 2005 and 7,184 mature firms (firm-age since IPO is at least 5 years) whose IPO date is either unknown or before 1975. For all 14,434 firms in the panel at least one quarterly total return is available from CRSP. The explanatory variables are the quarterly excess return of the value weighted CRSP index (RMRF), the return of a zero-investment size portfolio (SMB), the return of a zero-investment book-to-market portfolio (HML), and the return of a zero-investment momentum portfolio (MOM). In addition to these risk factors whose coefficient estimates and t-statistics are displayed in columns labeled with OLD, the regressions also contain a full set of interactions between the aforementioned factor variables and an IPO dummy variable. Thereby, the IPO dummy variable is defined according to the caption of the columns. The coefficient estimates and t-statistics for the interaction terms are presented in columns labeled with $\Delta(\mathrm{IPO} - \mathrm{OLD})$. As such, the coefficient estimate for the IPO dummy variable (which essentially is the interaction of the IPO dummy with the regression constant) is in row "Constant", the coefficient estimate for the $\mathrm{RMRF} \times \mathrm{IPO}$ interaction is in row "RMRF", etc. ***, **, * indicate significance at the 1, 5, and 10 percent level.

IPO occured	within the last year		within last 2 years		within last 3 years		within last 4 years		within last 5 years	
	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)
Constant	0.4081	-1.6818**	0.4635	-1.4050*	0.4344	-0.8311	0.3960	-0.5423	0.4183*	-0.5429
	(1.463)	(-2.041)	(1.620)	(-1.751)	(1.589)	(-1.078)	(1.606)	(-0.807)	(1.813)	(-0.904)
RMRF	0.9748***	0.2667**	0.9678***	0.2147***	0.9576***	0.2168***	0.9515***	0.1983***	0.9487***	0.1809***
	(27.612)	(2.439)	(28.275)	(3.061)	(30.055)	(3.638)	(31.645)	(3.319)	(32.622)	(3.230)
SMB	1.1243***	-0.0021	1.1055***	0.1426	1.0922***	0.1912	1.0717***	0.2452**	1.0456***	0.3233***
	(17.639)	(-0.010)	(17.648)	(0.950)	(18.649)	(1.499)	(19.740)	(2.333)	(20.762)	(3.101)
HML	0.1763***	-0.9025***	0.2199***	-0.9007***	0.2475***	-0.8170***	0.2745***	-0.7749***	0.2884***	-0.6902***
	(3.864)	(-6.521)	(4.712)	(-7.644)	(5.529)	(-7.551)	(6.255)	(-8.108)	(6.553)	(-7.910)
MOM	-0.0756	0.2361*	-0.0562	-0.0548	-0.0385	-0.1665	-0.0313	-0.1603	-0.0302	-0.1191
	(-1.300)	(1.847)	(-0.898)	(-0.374)	(-0.649)	(-1.190)	(-0.616)	(-1.301)	(-0.627)	(-1.097)
# obs.	524,914		524,914		524,914		524,914		524,914	
# firms	14,434		14,434		14,434		14,434		14,434	
R^2	0.126		0.128		0.129		0.129		0.129	

Table V

Firm characteristics and IPO performance

This table reports the coefficient estimates and t-values (in parentheses) from pooled OLS regressions with Driscoll-Kraay standard errors. The standard error estimates are heteroscedasticity consistent and robust to both cross-sectional dependence and autocorrelation up to four lags, respectively. In all regressions the firms' excess return (incl. distributions) over the *next* quarter is the dependent variable. The explanatory variables are obtained by aid of a Kronecker expansion between the factors of a Carhart (1997) model (i.e., market factor, SMB, HML, and MOM) and a set of firm characteristics (see Hoechle and Zimmermann, 2007). The firm characteristics considered are dummy variables being 1 for IPO firms who went public in a quarter with more than 101 IPOs (HOT) or less than 43 IPOs (COLD), respectively, the market leverage ratio (Leverage), the abnormal turnover which is defined as the difference between a stock's trading volume and the median trading volume of all stocks in the same size decile (ATurn), an industry-adjusted excess valuation measure that is based on the firms' sales (XVAL), and a dummy variable being one for firms reporting segments with differing NAICS codes in a given year (Diversified). In addition to these variables whose coefficient estimates and t-statistics are displayed in columns labeled with OLD, the regressions also contain a full set of interaction terms between the aforementioned explanatory variables and an IPO-dummy. The IPO-dummy is one for firms whose initial public offering took place within the last year. The coefficient estimates and t-statistics for the interaction variables are presented in columns labeled with $\Delta(\mathrm{IPO}-\mathrm{OLD})$. For brevity, the table only presents the estimation results for the firm characteristics (including the interactions with the IPO dummy). The sample data comprises an unbalanced panel of 7,378 firms going public between 1975 and 2005 and 7,184 mature firms (firm-age since IPO is at least 5 years) whose IPO date is either unknown or before 1975. In regressions which include the excess value measure (XVAL), we do only consider firm-quarters for which $abs(\mathrm{XVAL}) \leq 2.079$. ***, **, * indicate significance at the 1, 5, and 10 percent level.

	Issue Period		Leverage & Liquidity		Excess Valuation		Diversification		All (except expenditures)	
	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)
Constant	0.315	-2.828**	0.023	-2.711**	0.578**	-1.164**	0.687*	-1.827**	1.116**	-2.633*
	(0.945)	(-1.976)	(0.073)	(-2.126)	(2.033)	(-2.198)	(1.705)	(-2.088)	(2.002)	(-1.680)
HOT	-0.045	0.560							-0.022	0.284
	(-0.093)	(0.303)							(-0.038)	(0.193)
COLD	0.605	3.356							0.794	4.038*
	(1.065)	(1.344)							(1.113)	(1.957)
Leverage			0.085	1.053					-2.174***	-0.863
			(0.106)	(0.362)					(-2.631)	(-0.455)
ATurn			1.118**	-1.151					1.578***	-1.091
			(2.212)	(-1.529)					(3.176)	(-1.530)
XVAL					-2.432***	1.472*			-2.805***	1.517**
					(-11.881)	(1.856)			(-12.562)	(2.182)
Diversified							-0.719**	-1.333*	-0.537**	-0.850
							(-2.031)	(-1.861)	(-2.017)	(-0.917)
# obs.	524,914		422,492		427,969		426,975		360,545	
# firms	14,434		12,827		12,786		12,424		11,857	
R^2	0.128		0.142		0.132		0.128		0.150	

Table VI

Firm characteristics and IPO performance - Full specification and sample restrictions

This table reports the coefficient estimates and t-values (in parentheses) from pooled OLS regressions with Driscoll-Kraay standard errors. The standard error estimates are heteroscedasticity consistent and robust to both cross-sectional dependence and autocorrelation up to three lags, respectively. In all regressions the firms' excess return (incl. distributions) over the *next* quarter is the dependent variable. The explanatory variables are obtained by aid of a Kronecker expansion between the factors of a Carhart (1997) like performance measurement model and a set of firm characteristics (for details, see Hoechle and Zimmermann, 2007). The factors of the performance measurement model are the excess return of the CRSP value weighted index (incl. distributions), the return of a zero-investment book-to-market portfolio (HML), the return of a zero-investment size portfolio (SMB), and the return of a zero-investment momentum portfolio (MOM). The firm characteristics considered are a dummy variable being one if a company's business segments are located in two or more industries based on the NAICS code (Diversified), a dummy variable being 1 for IPO firms who went public in a quarter with more than 101 IPOs (HOT), a dummy variable being one for IPO firms whose initial public offering occurred in a quarter with less than 43 IPOs (COLD), the market leverage ratio (Leverage), the abnormal turnover which is defined as the difference between a stock's trading volume and the median trading volume of all stocks in the same size decile (ATurn), an industry-adjusted excess valuation measure that is based on the firms' sales (XVAL), the firms' quarterly capital expenditures scaled by sales (CAPEX), the firms' quarterly acquisitions scaled by sales (Acquisitions), and the firms' quarterly R&D expenditures scaled by sales (R&D). Since R&D is often missing, we replace missing values for R&D by 0 but include a dummy variable which equals 1 if R&D is missing in the regressions (missR&D). In addition to these explanatory variables whose coefficient estimates and t-statistics are displayed in columns labeled with OLD, the regressions also contain a full set of interaction terms between the aforementioned explanatory variables and an IPO-dummy. The IPO-dummy is 1 for firms whose IPO took place within the last year. The coefficient estimates and t-statistics for the interaction variables are presented in columns labeled with $\Delta(\mathrm{IPO} - \mathrm{OLD})$. For brevity, the table only presents the estimation results for the firm characteristics (including the interactions with the IPO-dummy). The sample data comprises an unbalanced panel of 7,378 firms going public between 1975 and 2005 and 7,184 mature firms (firm-age since IPO is at least 5 years) whose IPO date is either unknown or before 1975. While regressions 'Expenditures' and 'Full sample (1975 - 2005)' include all observations, the other regressions are based on restricted samples. Regression 'Valid link' constrains the sample to observations with a verified link between CRSP and COMPUSTAT, regression 'Period: 1975 - 1998' restricts the sample to the respective period, and regression 'NASDAQ firms only' does only include the subset of firms that are traded on the NASDAQ stock exchange. In regressions which include the excess value measure (XVAL), we do only consider firm-quarters for which $abs(\mathrm{XVAL}) \leq 2.079$. ***, **, * indicate significance at the 1, 5, and 10 percent level.

Table VI - continued

	Expenditures		Full sample (1975 - 2005)		Valid link		Period: 1975 - 1998		NASDAQ firms only	
	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)	OLD	Δ(IPO-OLD)
Constant	2.090***	-3.852***	1.469**	-2.637	0.930	-3.476	2.027***	-1.148	1.333	-0.062
	(3.808)	(-2.768)	(2.313)	(-1.440)	(1.052)	(-1.576)	(2.647)	(-0.609)	(1.509)	(-0.034)
CAPEX	-1.030**	-0.466	-0.423	-0.471	-0.611	-0.935	-1.384***	0.000	-0.538	-0.181
	(-2.251)	(-0.764)	(-0.871)	(-0.692)	(-0.930)	(-1.097)	(-2.647)	(0.000)	(-0.884)	(-0.166)
Acquisitions	-0.579**	0.375	-0.380	0.473	-0.978***	0.310	-0.379	0.525	-0.829**	1.172
	(-2.066)	(1.185)	(-1.333)	(1.215)	(-3.370)	(0.410)	(-1.491)	(1.120)	(-2.375)	(1.432)
R&D	-0.677	0.341	0.190	1.155	1.006	0.801	2.124	-1.885	0.165	2.021
	(-1.242)	(0.339)	(0.293)	(0.706)	(1.432)	(0.405)	(1.293)	(-1.289)	(0.256)	(1.163)
missR&D	-2.120***	2.754**	-1.712***	1.923**	-2.046***	2.076**	-1.505***	1.822**	-2.154***	2.052**
	(-3.693)	(2.109)	(-3.834)	(2.342)	(-3.656)	(2.198)	(-3.381)	(2.072)	(-3.796)	(2.174)
HOT			0.330	-0.394	0.255	-0.367	0.139	-0.912	0.356	-1.128
			(0.592)	(-0.255)	(0.305)	(-0.181)	(0.210)	(-0.615)	(0.445)	(-0.617)
COLD			1.331*	3.551*	1.198	4.180**	0.781	1.333	2.008*	4.770**
			(1.766)	(1.868)	(1.192)	(2.168)	(1.179)	(0.520)	(1.905)	(2.191)
Leverage			-0.806	-2.704	-0.239	-3.390	-0.939	-3.856*	3.050**	-8.467***
			(-0.854)	(-1.366)	(-0.218)	(-1.162)	(-0.829)	(-1.703)	(2.556)	(-3.515)
ATurn			1.534***	-1.186	1.652***	-2.767***	1.529***	-1.355	2.064***	-1.090
			(3.246)	(-1.485)	(3.102)	(-3.192)	(3.388)	(-1.161)	(3.037)	(-0.943)
XVAL			-2.867***	1.414**	-3.551***	2.286**	-2.734***	1.244***	-2.838***	1.141
			(-12.968)	(2.009)	(-14.953)	(2.443)	(-12.571)	(2.868)	(-9.033)	(1.055)
Diversified			-0.135	-1.037	0.231	-1.420	-0.438	0.525	-0.914***	-0.636
			(-0.567)	(-1.023)	(0.736)	(-0.818)	(-1.154)	(0.508)	(-3.221)	(-0.313)
# obs.	328,149		287,497		78,661		202,144		113,300	
# firms	11,491		10,885		4,419		9,275		4,309	
R^2	0.132		0.158		0.164		0.145		0.190	

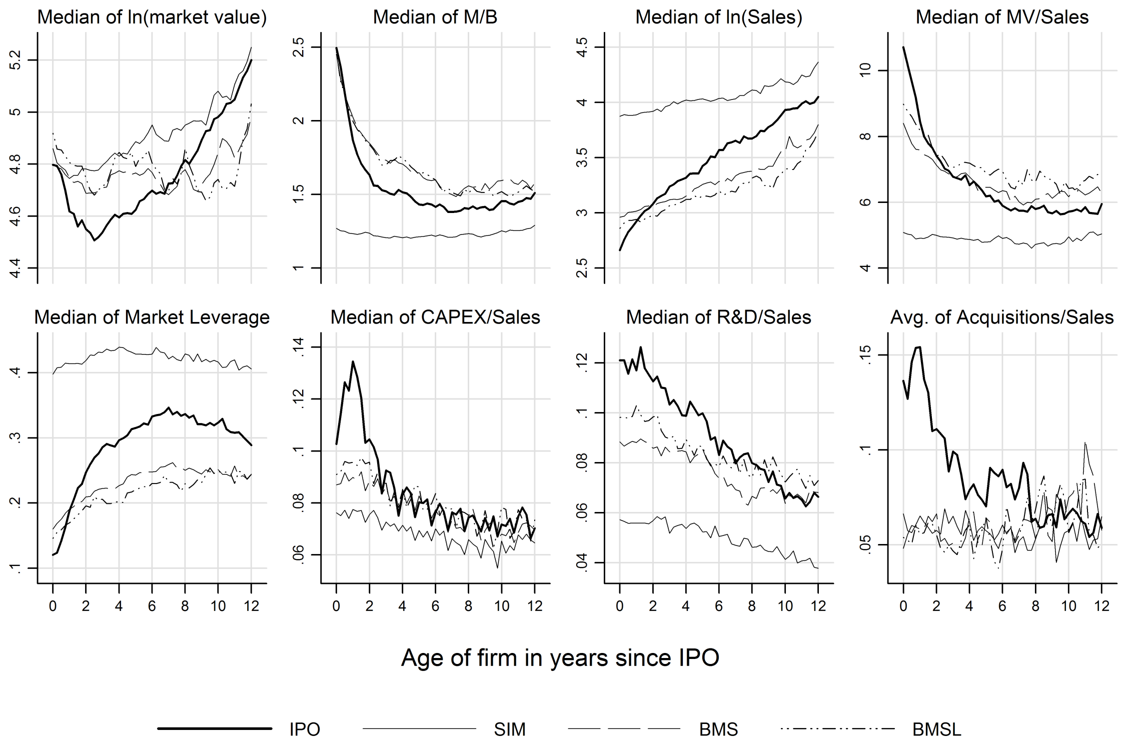

Figure 1. Evolution of firm characteristics in event time

Evolution of firm characteristics for 7,378 firms going public (IPO) between 1975 and 2005, and their non-issuing control firms matched on size (SIM) and size and book-to-market ratio without (BMS) and with (BMSL) validated link between CRSP and Compustat. Data on market capitalization and sales is in millions of 2005 USD.

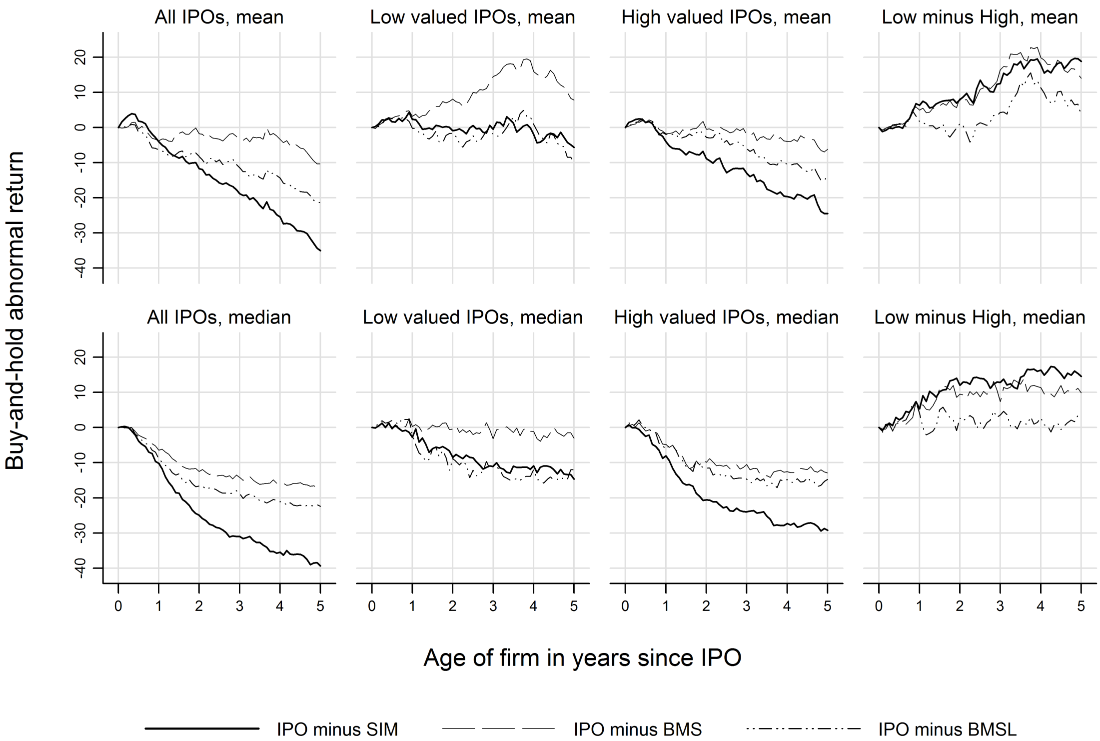

Figure 2. Buy-and-hold abnormal returns

Mean and median buy-and-hold abnormal returns (in %) for 6,828 firms going public (IPO) between 1975 and 2000, and their non-issuing control firms matched on size (SIM) and size and book-to-market ratio without (BMS) and with (BMSL) validated link between CRSP and Compustat. Low-valued IPOs have $-1.386 \leq \text{XVAL} \leq 0$, where XVAL refers to an industry adjusted excess valuation measure that is based on the firms' sales in the IPO quarter. High-valued IPOs have $0 < \text{XVAL} \leq 1.386$. IPOs with $abs(\text{XVAL}) > 1.386$ are recoded to have a missing excess value measure.

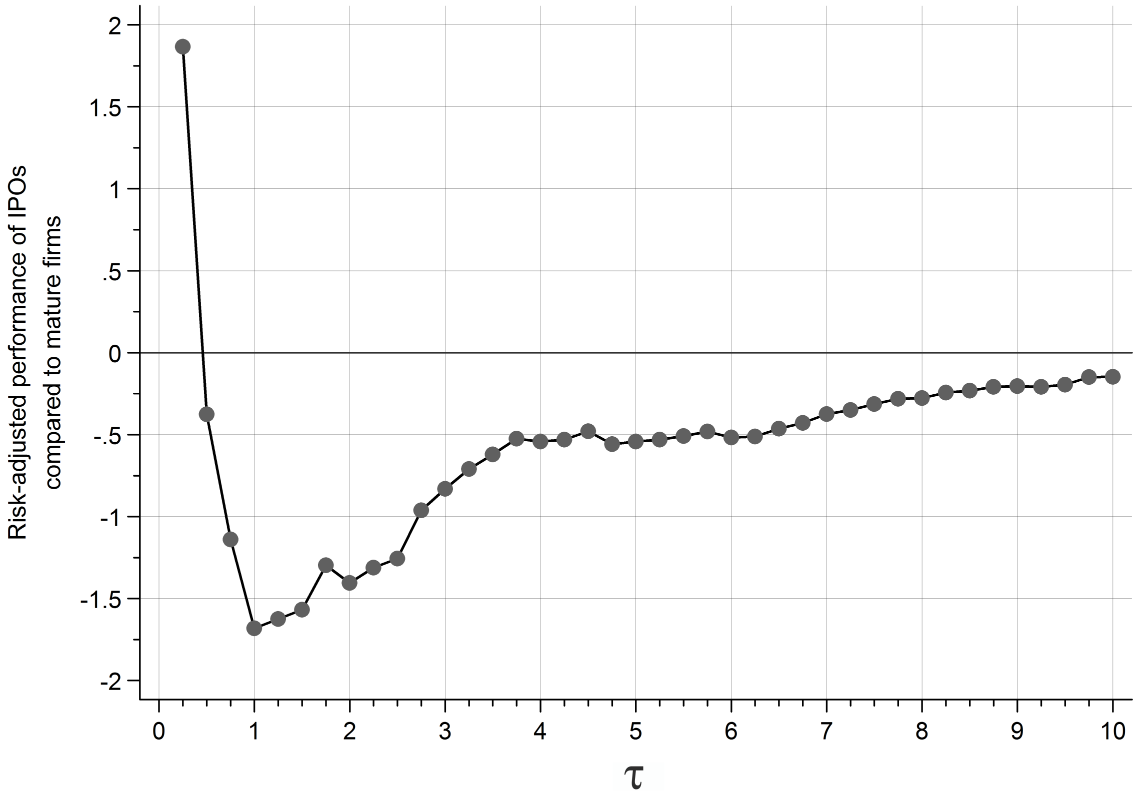

Figure 3. Risk-adjusted performance of "IPO firms"

The figure displays the quarterly difference between the risk-adjusted performance of IPO firms and that of more seasoned companies for 40 different definitions of "IPO firms" depending on the time horizon. The difference in risk-adjusted performance is measured by the coefficient estimate for the IPO dummy (D_{it}^{τ}) in regression (16). The IPO dummy is set to one for all firms going public within the last τ years and zero otherwise. The sample data comprises an unbalanced panel of 7,378 firms going public between 1975 and 2005 and 7,184 mature firms (firm-age since IPO is at least 5 years) whose IPO date is either unknown or before 1975.