



# Does idiosyncratic risk matter in IPO long-run performance?

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## Abstract

This paper studies how firm-level idiosyncratic risk varies over time and affects both initial public offering (IPO) and matched non-IPO firms' long-run performance. It revisits the traditional approach to compute the long-run performance by conditioning aftermarket performance on idiosyncratic risk with a generalized autoregressive conditional heteroskedasticity GARCH-M extension of the standard three-factor Fama and French (3FF) model. Our findings show a positive long-run relationship between idiosyncratic risk and expected returns for almost all IPOs and matched non-IPO firms. We find that, in general, IPOs do not underperform their peers when we adjust long-run abnormal returns for firm-level idiosyncratic risk. We also note that the idiosyncratic risk exposure depends on the IPO profile; it is more important for firms going public in hot-issue markets, undervalued IPOs and high idiosyncratic-risk issues. Thus, this paper suggests that a part of abnormal returns in specific IPOs long-run performance is derived from firm idiosyncratic risk.

**Keywords** Initial public offerings · Performance measures · Asset pricing · Idiosyncratic risk

**JEL Classification** G10 · G12 · G14

## 1 Introduction

The pricing of initial public offerings (IPOs) has attracted the attention of researchers in finance for decades. The literature identifies three anomalies in the IPO process. The first two anomalies observed in the short-run are, namely, the hot-issue market for IPOs (Ritter 1984) and IPO underpricing (Ritter and Welch 2002). The third anomaly is IPO long-run

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underperformance (Ritter 1991). Ritter (1991) and Loughran and Ritter (1995) report that IPOs underperform the market in the long run when they compare IPO stock returns to common market index returns.<sup>1</sup> Other empirical studies on IPO long-run performance present mixed results. Brav and Gompers (1997) and Gompers and Lerner (2003) do not find evidence of long-run IPO underperformance. Barber and Lyon (1997), Kothari and Warner (1997), and Gompers and Lerner (2003) document that IPO long-run performance depends on the methodology used to measure abnormal returns, which could explain the mixed evidence in the behavior of IPO performance.

We note that traditional approaches (cumulative abnormal returns (CAR) and buy-and-hold abnormal returns (BHAR)) to compute abnormal returns either do not account for risk or are only adjusted for the systematic risk associated with common risk factors (capital asset pricing model (CAPM)<sup>2</sup> and three-factor model of Fama and French (3FF)<sup>3</sup> 1993).

Despite the greater uncertainty associated with IPOs due to the absence of any traded firm value and the asymmetric information surrounding new issues (Rock 1986), previous studies (e.g., Ritter 1991; Brav and Gompers 1997) do not consider firm-level uncertainty in the measurement of IPO abnormal returns. Rock (1986), Benveniste and Spindt (1989) show that the presence of asymmetric information around new issues increases the complexity of the IPO pricing process. One exception is Beaulieu and Mrissa Bouden (2015a) who redefine the IPO cycles in terms of initial returns, IPO volume and issuing firms risk and show that the decision to go public depends on both market and issuing firm's uncertainties.

In the context of asset pricing models, Campbell and Taksler (2003) use idiosyncratic volatility to proxy for information asymmetry between the firm and market participants. Shleifer and Vishny (1997) show that stock mispricing depends heavily on the idiosyncratic risk component rather than the systematic one. Xu and Malkiel (2004) emphasize the important role of idiosyncratic volatility in explaining cross-sectional returns. In addition, they show that the predictive power of idiosyncratic volatility is higher than that of the "Beta". Goyal and Santa-Clara (2003) conclude that idiosyncratic risk is priced by showing that it is a better predictor of expected returns than total market variance.

In the context of IPOs, Lowry et al. (2010, p. 435) note that, "both the level and the uncertainty regarding individual firm initial returns are related to firm-specific sources of information asymmetry." In the early aftermarket stage, investors do not have sufficient information about the new issues, which explains the temporary destabilization in IPO activity in terms of returns and volatility.

Given these previous studies, we note that traditional measures of abnormal returns do not consider individual firm uncertainty and may include, in part, an anomaly associated with firm-level risk that could vary over time. Therefore, this study uses an approach that considers time-varying idiosyncratic volatility at the issuing firm level. In addition to gaining a better appreciation for IPO versus comparable non-IPO performance, this paper contributes to the IPO literature by using a generalized autoregressive conditional

<sup>1</sup> Loughran and Ritter (1995) use five common indices as benchmarks: (1) CRSP Amex-NYSE equally-weighted (EW) index, (2) CRSP Amex-NYSE value-weighted (VW) index, (3) S&P 500 price index (without dividend income), (4) CRSP NASDAQ equally-weighted (EW) index, and (5) CRSP NASDAQ value-weighted (VW) index.

<sup>2</sup> Abnormal returns computed from the CAPM are adjusted for the market risk factor.

<sup>3</sup> Abnormal returns computed from the 3FF model are adjusted for market, size, and book-to market risk factors.

heteroskedasticity GARCH-M (in mean) extension of the standard 3FF model to examine the relationship between idiosyncratic volatility and returns. Firm-level idiosyncratic volatility is associated with return movements due to new private information.<sup>4</sup> In this paper, we measure idiosyncratic risk by the conditional volatility of individual firm's returns<sup>5</sup> from the modified Fama and French model with GARCH-M (in mean) and tie it to specific firm risk factors.

The objective of the paper is to determine how firm-level idiosyncratic risk varies over time and affects both IPO and matched non-IPO firms' long-run performance. This paper also aims to assess the impact of firm-specific risk on IPO long-run performance controlling for some IPO characteristics that are associated with the level of issuing firm's idiosyncratic risk in the early aftermarket stage, IPO maturity, IPO underpricing, industry and the period of issuance.

The empirical results show a positive and significant relationship between firm-level idiosyncratic risk and IPO returns. Therefore, we find that abnormal returns in IPO long-run performance results are explained by firm idiosyncratic risk. Our results also show that most IPOs do not underperform their peers when long-run abnormal returns are adjusted for firm-level idiosyncratic risk. Furthermore, we note that high levels of underperformance are reported for high-idiosyncratic risk IPOs, such as technology issuers and hot new issues. Results also show that IPOs exhibit higher levels of idiosyncratic risk than matched non-issuing firms, especially in the early aftermarket stage. It is worth noting that IPO idiosyncratic risk decreases and approaches that of comparable established firms at the end of the third year of IPO trading. Finally, our findings show that the long-run exposure to IPO idiosyncratic risk varies according to: (1) risk characteristics of the issues: it is important for IPOs with high idiosyncratic volatility during the first quarter of IPO trading, (2) pre-IPO valuation (over- or undervalued IPOs with respect to their peers): it is insignificant for overvalued IPOs which are characterized by a high level of information asymmetry between issuers and investors who are then unable to correctly incorporate specific firm information into prices, and (3) across periods: it is important during hot markets which are characterized by a massive entry of high idiosyncratic risk firms. It vanishes however in the crisis period (from the end of 2007 to 2009) that dampens high idiosyncratic-risk firms from going public.

The remainder of the paper is organized as follows: The literature review and the hypotheses development are presented in Sect. 2. Data and matched firm selection are reported in Sect. 3. Section 4 presents the methodology and the empirical results. Section 5 discusses the implications for future research, potential investors, and decision makers. Section 6 concludes.

## 2 Literature review and hypotheses development

Previous studies, such as Ritter (1991), often measure long-run abnormal returns using classic event study methods, including CAR and BHAR, or the method of calendar-time portfolios based on Jensen's (1968) alpha from the CAPM. Abnormal returns measured by

<sup>4</sup> Lowry et al. (2010, p. 450) note that firm-specific volatility capture "the extent to which firm-specific information flows cause stock prices to move in different directions, or to change by different magnitudes".

<sup>5</sup> Fu (2009) uses the conditional volatility of individual returns from the exponential GARCH models to proxy for the idiosyncratic risk.

Jensen's alpha are "risk adjusted". Authors such as Spiegel and Wang (2005), frequently use the three-factor model of Fama and French with added risk factors (size and book-to-market ratio, among others) to the standard CAPM. Brav and Gompers (1997) note that the literature does not provide rational economic motivations for whether these factors [size, book-to-market, and momentum (Carhart 1997)] represent an equilibrium compensation for risk or an indication of market inefficiency. Therefore, the estimation of long-run abnormal returns continues to be sensitive to model choice as the problem of risk adjustment is still not satisfactorily resolved. This fact is underlined further by Kothari and Warner (2007) who note that the error in calculating abnormal performance is due to problems in adjusting for risk, especially in the long run.

Another important issue for measuring the long run performance of IPOs is the fact that the issuing firm does not have a historical record on the stock market. Therefore, the uncertainty associated with its fair value is higher for IPOs than for traded firms. To gauge the importance of risk in IPO long-run performance, we conduct a comparative study between IPOs and their matched peers in terms of long-run performance and firm-level risk. Previous studies, such as Ritter (1984) and Chiu (2005), often use total volatility to proxy for IPO risk. Hussein and Zhou (2014) use conditional return volatility as a risk measure and show that it produces a statistically significant positive effect on IPO initial returns, in addition to the traditional market, firm- and offer-specific characteristics. Our study isolates the risk component tied to the issuing firm specific characteristics given the asymmetric information that characterizes the IPO market. Unlike information associated with common market risk factors that are publicly available, some information about the issuer is not fully disclosed during the registration period. Hence, the informational disparity between issuers and investors, on the one hand, and informed investors and uninformed investors, on the other, is primarily due to lack in accessing specific information about the new issue. In this context, Guo (2005) emphasizes the role of the investor information that provides useful feedback for managers in the IPO market.

Previous literature shows that there is a relationship between idiosyncratic risk and returns. This is important since as discussed previously, idiosyncratic risk is often used to measure information asymmetry (Campbell and Taksler (2003)). Some empirical studies (Lintner 1965; Lehmann 1990; Beaulieu et al. 2005; Fu 2009) find a positive relationship between idiosyncratic volatility and returns. These authors argue that investors require a high premium for accepting the risk of holding high-idiosyncratic risk stocks. However, Arena et al. (2008) and Ang et al. (2006) show a negative relationship. Ang et al. (2006) explain the negative pricing of idiosyncratic risk in cross-sections by the fact that high-idiosyncratic risk stocks are more sensitive to market volatility risk, which lowers their returns. Vidal-García et al. (2016) also highlight the important role of the idiosyncratic risk factor in determining European fund performance. Hence, they note that more portfolios (mainly in Spain and Netherlands) positively load on idiosyncratic risk, while in the UK, all portfolios are significantly negative. In the case of IPOs, Beaulieu and Mrissa Bouden (2015b) find that firm-level idiosyncratic risk positively affects IPOs initial returns. In this paper, we investigate whether IPO-specific risk is important for long-run IPO pricing given the high information asymmetry in IPOs in their first 3 years of trading.

Based on the evidence in the literature, we stipulate that traditional measures of long-run abnormal returns, adjusted only for common risk factors, may include, in part, an abnormality associated with firm-level risk that is not necessarily stable over time. Previous authors (Engle 1982; Bollerslev 1986) account for the variation in the variance of returns over time by using the GARCH specification. Thus, we are motivated to revise previous methods used to compute IPO abnormal returns that assume a constant variance over

time. Hence, we are interested in modeling both the level and the variance in IPO long-run returns.

Furthermore, this study proposes refining the standard 3FF model by adding a GARCH-M extension. Our choice of model is motivated by the findings of the previous authors, Engle et al. (1987), who investigate the existence of a relationship between risk and expected returns. As a result, a variance term is added to the mean equation of the GARCH model to test for the significance of the risk-return relationship. This model jointly characterizes the evolution of the mean and the variance of time series returns. Engle et al. (1987) note that the variance of assets changes over time and affects the returns of the asset. Hence, the GARCH-M (in mean) model allows for a possible time-varying risk premium. Informed investors may require supplementary returns to hold the risky firm, motivating an additional risk premium associated with firm-specific risk since the GARCH-M (in mean) model is used at the firm level.<sup>6</sup> Since we assume that IPO specific risk varies over time as the information asymmetry resolves itself over time, we bring this GARCH-M (in mean) specification into our IPOs' long-run returns and risk. We test the following hypotheses:

**H<sub>0</sub>** Firm-level idiosyncratic risk does not affect expected long-run returns; as a result, abnormal performance estimates do not include abnormal returns associated with a firm-idiosyncratic risk premium.

**H<sub>1</sub>** Firm-level idiosyncratic risk significantly affects expected long-run returns; as a result, abnormal performance estimates partially include abnormal returns associated with a firm-idiosyncratic risk premium.

By examining the 3-year returns at the firm level, we focus on how idiosyncratic volatility risk, which is our proxy for new information about firm-specific risk factors, is incorporated into equity prices inducing changes in the long-run performance of IPOs versus their peers.

### 3 Data and matched firms selection

#### 3.1 IPO sample and data sources

Our sample consists of U.S. firms that issued ordinary common shares (codes 10 and 11) between January 2000 and December 2009. Following Brown and Kapadia (2007), IPOs with specific characteristics are excluded from the sample (i.e., units, closed-end funds, real estate investment trusts, American depositary receipts, and shares of beneficial interest). On Bloomberg, during this period, the number of ordinary common shares issued is 1440. However, our sample only includes IPOs whose returns are available from the Center for Research in Security Prices (CRSP) database and whose sales, EBITDA (earnings before interest, taxes, depreciation, and amortization), and EPS (earning per share) percentage change are available from the Compustat database industrial files (both active and research) during the quarter prior to the offer.

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<sup>6</sup> We follow Fu (2009) who uses the conditional variance, measured from the exponential GARCH model at the firm-level, as a proxy of the idiosyncratic risk.

After matching our sample with the available information in CRSP and Compustat, our final sample includes 571 IPOs. Of these IPOs, 19% went public in 2000, which is defined in the literature as a “hot-issue” market. The majority of new issues in 2000 (70%) are high-tech firms (Table 1).

### 3.2 Matching procedure and peer firm selection

Previous authors, such as Brav and Gompers (1997), often identify a control firm based on its closest IPO size (proxied by market capitalization) or/and book-to-market ratio. Bhojraj and Lee (2002) criticize the selection of control firms based on market value and book-to-market ratio due to the bias of the market price effect; it is well-known that IPO prices are supported by underwriters’ stabilization practices during the early aftermarket stage. In fact, Bhojraj and Lee (2002) suggest that a more accurate technique for selecting comparable firms is by isolating the pricing effect of other specific variables of interest to the researcher. In this framework, the market price does not necessarily reflect the (unobserved) intrinsic value of the firm.

Hence, in this study, we follow Bhojraj and Lee (2002) by matching firms in the same industry<sup>7</sup> based on their fundamentals (net sales,<sup>8</sup> EBITDA profit margin,<sup>9</sup> EPS percentage change,<sup>10</sup> and leverage ratio<sup>11</sup>), instead of market capitalization and book-to-market ratio, to avoid the market price effect.

We first consider all active firms on Compustat and research files for the fiscal year prior to the IPO year. Only firms that went public over the last 5 years since their IPO and issued ordinary common shares are included in our sample. Following Loughran and Ritter (2000), these firms are defined as non-issuing firms (non-IPOs) and compose our control sample. For this control sample, as well as for our IPO sample, we obtain SIC codes from CRSP as of the end of the prior calendar year and we group them into five industries using the industry classifications of Kenneth French.<sup>12</sup> We use the propensity score match<sup>13</sup> according to the nearest neighbor (greedy) matching method<sup>14</sup> to select the appropriate peer firm for each IPO based on firm fundamentals (industry, net sales, EBITDA profit margin, and EPS percentage change) during the quarter prior to the offer. As in Beaulieu

<sup>7</sup> Firms in the same industry have similar operating risks.

<sup>8</sup> Net sales are an ex-ante proxy for size.

<sup>9</sup> EBITDA profit margin is a proxy for profitability.

<sup>10</sup> EPS percentage change is a proxy for growth perspectives.

<sup>11</sup> Leverage ratio is a proxy for capital structure.

<sup>12</sup> CNMR includes sustainable and unsustainable consumption, wholesale, retail, and some services (laundries, repair shops). MANUF includes manufacturing, energy, and utilities. HITEC includes business facilities, telephone, and television transmission. HLTH includes healthcare, medical equipment, and medicines. OTHER includes mining, construction, transportation, hotels, services, entertainment, and the financial sector. The industry classification is based on the website of Kenneth R. French (<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>).

<sup>13</sup> The propensity score matching method is based on the propensity score  $e(X_i)$ . The propensity score is the conditional probability of a non-IPO of being assigned to a particular IPO given a vector of observed characteristics ( $X_i$ ):  $e(X_i) = Pr(Z_i = 1|X_i)$ . The propensity scores are estimated by a logistic regression. The dependent variable is binary:  $Z_i = 1$  for treatment (IPO) and  $Z_i = 0$  for control (non-IPO).

<sup>14</sup> The greedy nearest neighbor (Ho et al. 2011) is a version of an algorithm that selects a treatment group and a control group for the closest match. We choose the following options: one-to-one matching (selecting one matched non-IPO for each IPO) and sampling with replacement (once a non-IPO has been matched, it can be reused in another match).

**Table 1** IPO sample

Year	Number of issues	Returns available in CRSP and Data on net sales, EBITDA and EPS available in COMPUSTAT	INDUSTRIES				
			CNSMR	HITEC	HLTH	MANUF	OTHER
2000	323	108	3	76	14	6	9
2001	85	27	4	8	9	2	4
2002	84	33	10	10	5	0	8
2003	88	31	4	8	2	1	16
2004	228	96	13	25	25	7	26
2005	197	78	15	19	12	11	21
2006	173	71	10	14	16	9	22
2007	174	87	5	33	16	8	25
2008	30	16	0	2	3	2	9
2009	58	24	2	3	3	1	15
Total	1440	571	66	198	105	47	155

This table reports descriptive statistics on our IPO sample. We provide the number of IPOs per year and industry during the period 2000 and 2009. Each NYSE, AMEX, and NASDAQ IPO stock is assigned to an industry portfolio based on its four-digit SIC code (we use Compustat SIC codes for the fiscal year ending). The industrial classification is based on the website of Kenneth R. French (<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>). Our IPO sample is classified into five industries: (1) CNSMR includes sustainable and unsustainable consumption, wholesale, retail, and some services (laundries, repair shops), (2) MANUF includes manufacturing, energy and utilities, (3) HITEC includes business facilities, telephone and television transmission, (4) HLTH includes health care, medical equipment and medicines, and (5) OTHER includes mining, construction, transportation, hotels, services, entertainment and the financial sector. Net Sales, EBITDA and EPS are obtained from Compustat during the quarter prior to the offer. EBITDA represents Earnings Before Interest and Taxes and Depreciation (Quarterly) (Net Sales less Cost of Goods Sold and Selling, General, and Administrative Expense before deducting Depreciation, Depletion, and Amortization). EPS represents Earnings Per Share percentage change divided by Net Sales (Quarterly)

**Table 2** IPOs versus propensity score matched firm characteristics

Matching criteria	IPO firms				Matched firms				Mean Diff.	SB (%)		
	N	Mean	25%	Median	75%	N	Mean	25%			Median	75%
<i>ISPL Matching</i>	844					844						
Net Sales (\$ Millions)		122.10	7.76	26.25	85.20		122.52	7.97	26.45	85.08	-0.42	-0.10
EBITDAM (\$ Millions)		-351.78	-10.30	10.10	22.27		-185.35	-1.54	10.05	23.24	-166.43	-7.97
<i>ISPG Matching</i>	571					571						
Net Sales (\$ Millions)		91.41	6.91	24.49	71.68		92.53	8.00	24.48	75.74	-1.11	-0.44
EBITDAM (\$ Millions)		-364.28	-25.31	8.97	20.56		-447.06	-3.81	9.60	21.79	82.77	1.61
EPS (%)		24.4572	-46.79	18.51	80.00		25.73	-31.10	15.80	68.08	-1.27	-0.63
<i>ISPL Matching</i>	538					538						
Net Sales (\$ Millions)		84.83	6.58	23.12	67.28		100.52	7.44	22.09	84.51	-15.69	-6.77
EBITDAM (\$ Millions)		-387.18	-29.45	8.42	19.65		-73.59	-0.53	10.55	20.94	-313.59	-14.36
EPS (%)		27.77	-46.06	17.44	79.35		44.572	-22.34	16.73	76.63	-16.79	-8.28
LEVERAGE (%)		49.82	0.00	20.08	104.50		42.79	0.00	14.12	74.36	7.03	3.67

This table compares firm fundamentals (Net Sales, EBITDAM, EPS and LEVERAGE) of an IPO portfolio with their matching firms according to three matching alternatives (*Industry/Size/Profitability ISPL Matching*, *Industry/Size/Profitability/Growth ISPG Matching* and *Industry/Size/Profitability/Growth/Risk ISPL Matching*). Propensity score match is used to match one IPO with a single established firm (non-IPO). Net Sales, EBITDAM, EPS and LEVERAGE are obtained from Compustat. The industrial classification is based on the website of Kenneth R. French. SB (standardized difference) is the difference of the average value of a given covariate between the IPO and control group divided by the square root of the average variance between the IPO and control group



and Mrissa Bouden (2015b), we use three matching procedures to select matched firms: (1) Industry/Size/Profitability, (2) Industry/Size/Profitability/Growth, and (3) Industry/Size/Profitability/Growth/Leverage.

Table 2 shows that the second matching procedure (Industry/Size/Profitability/Growth) produces matched firms closest to our IPO sample as it provides the lowest levels of standardized differences (SD) between the IPO and control firms. Hence, we retain non-IPO firms matched according to industry, net sales, EBITDA profit margin, and EPS percentage change as the peer firms of our IPO sample.

## 4 Methodology and empirical results

### 4.1 IPO versus non-IPO long-run performance from the standard three-factor model

We use the following standard three-factor model (3FF) of Fama and French (1993) to compare the individual long-run performance of the IPO with respect to its comparable non-IPO equity over the event time.

$$R_{i,j} - R_{f,j} = \alpha_i^{FF} + \beta_{MKT_i}(R_{m,j} - R_{f,j}) + \beta_{SMB_i}SMB_j + \beta_{HML_i}HML_j + \epsilon_{i,j} \quad (1)$$

where  $(R_{i,j} - R_{f,j})$  is the stock excess return for firm  $i$  relative to the risk-free rate on event day  $j$ ; the intercept  $(\alpha_i^{FF})$  measures the individual abnormal return for stock  $i$  during the first 3-year period of the equity.  $(R_{m,j} - R_{f,j})$ ,  $SMB_j$  and  $HML_j$  are the market, size and book-to-market factors, respectively.

Table 3 shows the mean, the median and the quartiles of the coefficients estimated from the standard three-factor (3FF)<sup>15</sup> model  $(\alpha_i^{FF}, \beta_{MKT_i}, \beta_{SMB_i}$  and  $\beta_{HML_i})$  for individual IPO and matched non-IPO equities during the first 3 years of IPO trading.

First, results show positive and significant values for the mean and the median of the alpha distribution for both IPOs (0.28 and 0.40, respectively) and their peers (0.31 and 0.41, respectively). We start by analyzing the level of IPO long-run performance relative to the market (via the alpha coefficient) and then compare it with that of their matched non-issuers (via the difference in alpha coefficients between IPOs and their non-IPO peers). On the one hand, we note that the positive average values of the alpha coefficients for IPOs are not consistent with the previous findings of Loughran and Ritter (1995, p. 45) who show that large and small issuers underperform the market by, respectively, 21 and 34 basis points per month. Moreover, we add that the alpha distribution in our sample exhibits a mean lower than the median, indicating a distribution skewed to the left for both type of equities (IPOs and non-IPOs). On the other hand, our findings show that IPOs exhibit lower average values of the alpha coefficients than those of comparable non-issuing firms. This finding is consistent with Loughran and Ritter (1995) who show that large and small issuers respectively underperform large and small non-issuers by 24 and 26 basis points per month. Our standard three-factor (3FF) regression results also support previous findings in the IPO literature (Ritter 1991; Loughran and Ritter 1995) showing that issuing firms underperform their peers over the first 3 years of IPO trading. Although our results differ

<sup>15</sup> We also use the fourth-factor model of Carhart (1997). Results from both models (3FF and Carhart) are not significantly different from the one presented in this paper.

**Table 3** Distribution of the coefficients from the standard three-factor model used for individual equities: IPOs versus matched non-IPOs

Coefficients	IPOs					non-IPOs					DIFF: (coeff. <sub>IPO</sub> - coeff. <sub>non-IPO</sub> )					
	25%	MEAN	MED	75%	25%	MEAN	MED	75%	25%	MEAN	MED	75%	25%	MEAN	MED	75%
<i>Alpha</i>	$-0.45 \times 10^{-3}$	$0.28 \times 10^{-3}$	$0.40 \times 10^{-3}$	$1.08 \times 10^{-3}$	$-0.22 \times 10^{-3}$	$0.31 \times 10^{-3}$	$0.41 \times 10^{-3}$	$1.16 \times 10^{-3}$	$-1.28 \times 10^{-3}$	$-0.01 \times 10^{-3}$	$-0.08 \times 10^{-3}$	$1.02 \times 10^{-3}$				
<i>t-test (p value)</i>		(<0.0001)				(0.0853)				(0.0950)						
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				(0.0836)						
<i>Beta<sub>MKT</sub></i>	0.59	0.90	0.86	1.21	0.29	0.75	0.72	1.15	-0.33	0.16	0.15	0.67				
<i>t-test (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)						
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)						
<i>Beta<sub>SMB</sub></i>	0.42	0.82	0.79	1.16	0.17	0.59	0.58	1.07	-0.36	0.23	0.21	0.79				
<i>t-test (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)						
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)						
<i>Beta<sub>HML</sub></i>	-0.38	-0.06	-0.03	0.33	-0.33	0.02	0.05	0.40	-0.60	-0.08	-0.05	0.43				
<i>t-test (p value)</i>		(0.0400)				(0.5725)				(0.0824)						
<i>Wilcoxon (p value)</i>		(0.0932)				(0.0703)				(0.0261)						
<i>N</i>																

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This table reports the mean, the median and the quartiles of the coefficients estimated from the standard three-factor (3FF) model (see Eq. (1) of Fama and French (1993), for individual IPOs and matched non-IPOs' equities during the first 3 years of IPO trading. This model is estimated for IPO and matched non-IPO individual stocks during the first 3 years of IPO trading.  $\beta_{MKT}$ ,  $\beta_{SMB}$ , and  $\beta_{HML}$  are the respective sensitivities of the individual expected returns to the market ( $R_{m,t} - R_{f,t}$ ), size (SMB<sub>*t*</sub>) and book-to-market (HML<sub>*t*</sub>) factors. The intercept  $\alpha_{i,t}^{FF}$  measures the individual 3-year abnormal returns adjusted for common systematic risk factors (market, size and book-to-market). The non-IPOs equities are selected based on industry, sales, profitability and growth similar to those of the IPOs equities using the propensity score matching method. The Wilcoxon signed rank test is presented as a non-parametric alternative to the t-test when the data cannot be assumed normally distributed. The one-sample t-test (Wilcoxon signed rank test) is used to determine whether the mean (median) of the sample is equal to zero ( $H_0: \mu = 0$ ). The two sample t-test is used to compare the difference between two means to zero ( $H_0: \mu \text{ of the difference} = 0$ ). The Wilcoxon signed-rank test for two samples is used to test the null hypothesis that the two distributions are identical against the alternative hypothesis that the two distributions differ only with respect to the median. Values in parentheses correspond to the *p* values of t-test and Wilcoxon signed rank test

from the ones documented in the earlier literature in terms of IPOs performance compared to the market, they are consistent with them when we document IPOs performance to compare it with matched non IPOs.

Second, Table 3 shows positive and significant values for the mean and the median of the  $\beta_{MKT_i}$  distribution for both IPOs (0.90 and 0.86, respectively) and their peers (0.75 and 0.72, respectively). We note a positive and significant difference between  $\beta_{MKT}^{IPO_i}$  and  $\beta_{MKT}^{non-IPO_i}$  indicating that issuing firms are more sensitive to the market factor than their matched peers. This result confirms Loughran and Ritter (1995, p. 46) who note that issuing firms exhibit slightly higher betas than non-issuing firms. Similar results are shown for the distribution of Betas associated with the size factor ( $\beta_{SMB_i}$ ). However, we note a weak book-to-market effect. The majority of IPOs (70% and 79% of matched non-IPOs) have a negligible  $\beta_{HML_i}$ . Results show that unlike non-issuing firms, IPOs exhibit a negative mean for the distribution of Betas associated with the book-to-market factor ( $\beta_{HML_i}$ ). This finding could be explained by the fact that IPOs may have a lower book-to-market ratio<sup>16</sup> relative to the one of comparable non-issuing equities, resulting from a possible overvaluation of the IPO by the market participants especially during the lock-up period.<sup>17</sup>

Nevertheless, we recognize that the standard 3FF model only includes systematic risk factors and does not account for the possible firm-level risk effect on long-run returns. Therefore, the intercept from the standard 3FF is adjusted for systematic risk factors only and could contain, in part, a premium associated with firm-level risk. If idiosyncratic risk is priced, then the alpha from the standard 3FF model ( $\alpha_i^{FF}$ ), even if it is zero for the majority of IPOs, could mask a more important abnormal performance. Therefore, we require a more complete measure of abnormal returns adjusted for the premium associated with idiosyncratic risk. This leads us to revise the methodology for measuring long-run abnormal returns in the following sections.

## 4.2 Three-year idiosyncratic risk-return cross-section correlation

This section investigates a possible relationship between firm-level idiosyncratic risk and long-run aftermarket returns. Following the analysis of Spiegel and Wang (2005), we use the variance in the 3FF model residuals during the first 3 years of offering (T = 3 years) to compute the realized idiosyncratic variance  $\left[ RIV_i^T = VAR(\varepsilon_{ij}^T) \times 10^4 \right]$  for firm  $i$ .

We expect that the magnitude of the relationship between idiosyncratic risk and long-run IPO returns will vary from one period to another. Bozhkov et al. (2018) compare the significance of idiosyncratic volatility in different market environments given that some studies (John and Harris 1990) document that stock response differs according to the level of stress associated with the period. For example, Bozhkov et al. (2018) show a stronger correlation between idiosyncratic risk and returns during recessions, especially when investors are more risk averse. Thus, it seems that there is an interaction between risk premium and risk tolerance varying given the market environment. This motivates our analysis of the relationship between firm idiosyncratic risk and long-run IPO returns across different periods. Based on the results of Beaulieu and Mrissa Bouden (2015a), we split our

<sup>16</sup> Fama and French (1993, p. 20) show that HML slopes switch regularly from negative values for the lowest book-to-market quintile to positive values for the highest book-to-market quintile.

<sup>17</sup> Insiders are generally informed investors prohibited from selling the stock during the IPO lock-up period that usually lasts from 90 to 180 days after the company goes public.

sample in three issuance sub-periods according to average IPOs initial returns, the volatility of IPOs initial returns, and the number of issued IPOs: (1) a hot-issue IPO market in 2000 which is characterized by the highest level in IPO volume, IPO initial returns and IPO risk,<sup>18</sup> (2) a quiet IPO market between 2001 and 2007 which is characterized by a medium level of IPO volume and relatively weak IPO initial returns and risk, and (3) a crisis period for IPOs at the end of 2007 (the start of the American recession) to 2009 characterized by the lowest level of IPO volume, and a relatively unstable IPO initial returns and risk (with peaks by the end of 2007).

Table 4 shows Pearson, Spearman, and Kendall correlations between: (1) average 3-year IPO excess returns relative to the risk-free rate  $\left(R_{ij}^{IPO} - R_{f,j}\right)_{\{j=756days\}}$  and IPO realized idiosyncratic variance  $RIV_{ij}^{IPO}_{\{j=756days\}}$ , and (2) average 3-year IPO excess returns relative to the matched non-IPO  $\left(R_{ij}^{IPO} - R_{ij}^{non-IPO}\right)_{\{j=756days\}}$  and IPO excess idiosyncratic variance  $\left(RIV_{ij}^{IPO} - RIV_{ij}^{non-IPO}\right)_{\{j=756days\}}$ .

First, we note that in the hot-issue market IPOs exhibits negative 3-year excess returns ( $-0.04\%$ ) and lower 3-year excess returns than that of matched non-issuing firms. This result confirms the market-timing hypothesis of Loughran and Ritter (2000) who argue that issues in high-volume periods are more likely to underperform in the long run.

More interestingly, we note that there is a negative correlation between IPO idiosyncratic risk and IPO long-run returns for the overall IPO sample. This finding is consistent with Ang et al. (2006) and Arena et al. (2008) who show a negative relationship between idiosyncratic risk and cross-section returns for traded firms. We add that the magnitude of the relationship between IPO idiosyncratic risk and IPO long-run returns is more important during the hot-market and crisis periods. However, we note that this relationship is insignificant during the quiet period.

Moreover, Table 4 shows a positive (negative) cross-section Pearson correlation between IPO 3-year abnormal returns and their idiosyncratic abnormal risk compared to their peers during the hot-issue market (crisis), suggesting the existence of a significant linear relationship between these variables. However, the sign of this linear relationship differs according to the issuance period. It seems that investors continue to hold risky issues by requiring an IPO excess idiosyncratic risk premium in periods of high IPO volume. However, they are more risk averse during the crisis and tend to sell IPOs characterized by an excess idiosyncratic risk compared with their peers, which lowers their prices in the long run. Thus, it is interesting to investigate the relationship between abnormal returns and abnormal idiosyncratic risk through time because investors risk behavior may change over time.

Since our findings confirm a long-run relationship between IPO idiosyncratic risk and aftermarket returns with different magnitude depending on the issuance periods, we stipulate that abnormal returns computed from the standard 3FF model may include, in part, a risk premium associated with firm specific risk. Therefore, we propose in the next sections a new model to measure long-run abnormal return that accounts for a long-run idiosyncratic risk-return relationship.

<sup>18</sup> (1) IPO volume is measured by the total number of IPOs in each month, (2) IPO initial returns are measured by the percentage difference between the closing price of the first transaction day and the offer price, and (3) IPO risk is measured by the variance of excess IPO returns relative to the risk-free rate during the first month of IPO trading (see Beaulieu and Mrissa Bouden (2015a, p. 11).

**Table 4** Three-year idiosyncratic risk-return cross-section correlation for firms going public Between 2000 and 2009

Time-series variables	N	Mean %	Median %	STD %	Correlation		
					Pearson	Spearman	
Kendall							
<i>2000: IPOs in hot period</i>							
$\overline{(R_j^{IPO} - R_{ij})}_{j=1, \dots, N, j=756 \text{ days}}$	108	-0.04	-0.02	0.21	-0.2438 (0.0110)	-0.2326 (0.0154)	-0.1613 (0.0133)
$RIV_j^{IPO} \text{ (}_{j=1, \dots, N, j=756 \text{ days}})$	108	57.60	46.00	44.9			
$\overline{(R_{ij}^{IPO} - R_{ij}^{non-IPO})}_{(j=756 \text{ days})}$	108	-1.35	-1.25	0.34	0.2964 (0.0021)	0.0193 (0.8448)	0.011 (0.8637)
$(RIV_{ij}^{IPO} - RIV_{ij}^{non-IPO})_{(j=756 \text{ days})}$	108	17.2	18.6	0.73			
<i>2001–2007: IPOs in quiet period</i>							
$\overline{(R_{ij}^{IPO} - R_{ij})}_{(j=756 \text{ days})}$	423	0.04	0.05	0.12	-0.0311 (0.5224)	-0.1168 (0.0162)	-0.0806 (0.0132)
$RIV_{ij}^{IPO} \text{ (}_{j=756 \text{ days}})$	423	14.70	10.90	15.00			
$\overline{(R_{ij}^{IPO} - R_{ij}^{non-IPO})}_{(j=756 \text{ days})}$	423	0.01	0.01	0.29	0.0374 (0.4482)	-0.0452 (0.3592)	-0.0335 (0.3092)
$(RIV_{ij}^{IPO} - RIV_{ij}^{non-IPO})_{(j=756 \text{ days})}$	423	-4.35	1.09	0.41			
<i>2008–2009: IPOs in crisis period</i>							
$\overline{(R_{ij}^{IPO} - R_{ij})}_{(j=756 \text{ days})}$	40	0.07	0.07	0.09	-0.2816 (0.0783)	-0.2819 (0.0779)	-0.1871 (0.0889)
$RIV_{ij}^{IPO} \text{ (}_{j=756 \text{ days}})$	40	9.38	7.23	7.82			
$\overline{(R_{ij}^{IPO} - R_{ij}^{non-IPO})}_{(j=756 \text{ days})}$	40	0.10	-0.01	1.00	-0.7120 (<0.0001)	0.1071 (0.5106)	0.0667 (0.5446)
$(RIV_{ij}^{IPO} - RIV_{ij}^{non-IPO})_{(j=756 \text{ days})}$	40	-18.5	-2.84	0.48			

**Table 4** (continued)

Time-series variables	N	Mean %	Median %	STD %	Correlation	
					Spearman	Kendall
<i>2000–2009: IPOs in overall period</i>						
$\left( \overline{R_{ij}^{IPO}} - R_{ij} \right)_{(j=756 \text{ days})}$	571	0.02	0.04	0.14	-0.2507 (<0.0001)	-0.2286 (<0.0001)
$RIV_{ij}^{IPO} \text{ }_{(j=756 \text{ days})}$	571	22.50	12.50	29.00		
$\left( \overline{R_{ij}^{IPO}} - \overline{R_{ij}^{\text{non-IPO}}} \right)_{(j=756 \text{ days})}$	571	-0.00	-0.01	0.40	-0.0649 (0.1254)	-0.0630 (0.1369)
$(RIV_{ij}^{IPO} - RIV_{ij}^{\text{non-IPO}})_{(j=756 \text{ days})}$	571	-1.31	1.66	0.50		

This table shows the mean, median, standard deviation (STD) and cross-section correlation of: (1) average 3-year IPO excess returns relative to the risk-free rate  $\left( \overline{R_{ij}^{IPO}} - R_{ij} \right)_{(j=756 \text{ days})}$  and the realized IPO idiosyncratic variance  $RIV_{ij}^{IPO}$  during the first 3 years of offering, and (2) average 3-year IPO excess returns relative to the matched non-issuing firm  $\left( \overline{R_{ij}^{IPO}} - \overline{R_{ij}^{\text{non-IPO}}} \right)_{(j=756 \text{ days})}$  and the three-year IPO excess idiosyncratic variance relative to the matched non-issuing firm  $(RIV_{ij}^{IPO} - RIV_{ij}^{\text{non-IPO}})_{(j=756 \text{ days})}$ . The 3-year realized idiosyncratic variance  $RIV^i$  for a firm  $i$  is computed on the basis of the variance of standard three-factor (3FF) model's residuals as follows:  $RIV^i = VAR(\epsilon^i) \times 10^4$  ( $i = 1, \dots, 571$ ). The non-issuing firms are selected based on industry, sales, profitability and growth similar to those of the issuing firms using the propensity score matching method. We split our IPO sample into three sub-periods: (1) IPOs in hot period (between 2001 and 2007) and (3) IPOs in crisis period (between 2008 and 2009). We use three tests of correlation: (1) the parametric test of Pearson  $r$  correlation that measures the degree of the relationship between linearly related variables, (2) the non-parametric test of Spearman rank correlation that does not assume any assumptions about the distribution of the data and measure the degree of association between two variables and (3) the non-parametric test of Kendall rank correlation that measures the strength of dependence between two variables. Values in parentheses correspond to the  $p$  values associated with correlation tests under [ $H_0: Rho=0$  (Pearson),  $Rho=0$  (Spearman) and  $Tau=0$  (Kendall)]

### 4.3 Conditional idiosyncratic volatility impact on the long-run performance

This section focuses on a model that incorporates time-varying volatility to better measure long-run abnormal performance. Such models, known as autoregressive conditional heteroskedasticity (ARCH) models, introduced by Engle (1982), model financial time series that exhibit time-varying volatility. Bollerslev (1986) suggests a generalized ARCH (GARCH) model that assumes an autoregressive moving average (ARMA) model for the error variance. The previous literature allows for time-varying volatility by including modifications to the standard models to consider the GARCH effect around an event (Böhmer et al. 1991). These authors argue that “when an event causes even minor increases in variance, the most commonly-used methods reject the null hypothesis of zero average abnormal return too frequently when it is true” (p. 253).

In the context of an IPO short-run perspective, Lowry et al. (2010) estimate not only the level but also the variance of IPO initial returns. They show an increasing volatility during the early aftermarket stage, especially during the hot-issue market. Hence, it is interesting to focus on the level as well as the variance of returns for the IPO long-run perspective to show whether time-varying firm-level risk affects the long-run abnormal performance measurement. Beaulieu and Mrissa Bouden (2015) show that short run IPO mispricing in pre (registration period)—and post (first-day of IPO trading)—IPO is explained by idiosyncratic risk. Therefore, we argue that market participants should be compensated for systematic as well as for firm-level risk. Hence, we focus in this section on a model that incorporates time-varying conditional firm-level risk to show how firm-level risk affects IPO and similar non-IPO long-run returns and causes changes in IPO’s long-run abnormal performance. Our objective is to highlight the part of the abnormal performance due to firm-level risk exposure.

We present the modified 3FF model with GARCH-M (in mean) extension for the daily individual excess returns over the IPO event-time as follows:

$$R_{i,j} - R_{f,j} = \alpha_i^{FF\_GARCH-M} + \beta_{MKT_i}(R_{m,j} - R_{f,j}) + \beta_{SMB_i}SMB_j + \beta_{HML_i}HML_j + \delta_i \sqrt{h_{i,j}} + \varepsilon_{i,j}, \quad (2)$$

where  $\varepsilon_{i,j} = \sqrt{h_{i,j}}z_{i,j}$  with a Gaussian innovation distribution,

$$h_{i,j} = \gamma_i + \theta_i h_{i,j-1} + \eta_i \varepsilon_{i,j-1}^2. \quad (3)$$

$i$  represents each equity: (i) IPO or (ii) comparable non-IPO and  $j$  corresponds to IPO event day.

This model is estimated for IPO and matched non-IPO individual stocks during the first 3 years of IPO trading. The conditional variance  $h_{i,j}$  from the model measures the firm-level conditional idiosyncratic risk (Beaulieu et al. 2005; Fu 2009). The sensitivity of expected returns to conditional idiosyncratic volatility is  $\delta_i$  and it measures the long-run returns’ exposure to the firm-level idiosyncratic risk. The abnormal return for stock  $i$  is measured by: (1) the intercept ( $\alpha_i^{FF\_GARCH-M}$ ), which is adjusted for systematic risk factors (market, size, and book-to-market) as well as firm-level idiosyncratic risk, and (2) the part associated with the firm-level idiosyncratic risk exposition ( $\delta_i \sqrt{h_{i,j}}$ ).

The empirical results in Table 5 show negative values for the mean and the median of alpha computed from the modified 3FF with GARCH-M for both IPOs (−0.58 and −0.06,

**Table 5** Distribution of the coefficients from the modified three-factor model used for individual equities: IPOs versus matched non-IPOs

Coefficients	IPOs						non-IPOs						DIFF. ( $\alpha_{IPO} - \alpha_{non-IPO}$ )					
	25%	MEAN	MED	75%	25%	MEAN	MED	75%	25%	MEAN	MED	75%	25%	MEAN	MED	75%		
<i>Alpha</i>	$-1.99 \times 10^{-3}$	$-0.58 \times 10^{-3}$	$-0.06 \times 10^{-3}$	$1.50 \times 10^{-3}$	$-1.70 \times 10^{-3}$	$-0.42 \times 10^{-3}$	$-0.11 \times 10^{-3}$	$0.91 \times 10^{-3}$	$-2.62 \times 10^{-3}$	$-0.17 \times 10^{-3}$	$0.09 \times 10^{-3}$	$2.91 \times 10^{-3}$						
<i>t-test (p value)</i>		(0.2519)				(0.1458)				(0.6657)								
<i>Wilcoxon (p value)</i>		(0.1498)				(0.0033)				(0.5261)								
<i>Beta<sub>MKT</sub></i>	0.53	0.84	0.83	1.15	0.23	0.71	0.70	1.11	-0.33	0.14	0.14	0.69						
<i>t-test (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)								
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)								
<i>Beta<sub>SMB</sub></i>	0.35	0.76	0.77	1.12	0.12	0.58	0.58	1.04	-0.40	0.20	0.21	0.75						
<i>t-test (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)								
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				(<0.0001)								
<i>Beta<sub>HML</sub></i>	-0.40	-0.06	-0.01	0.31	-0.26	0.05	0.06	0.35	-0.64	-0.12	-0.07	0.43						
<i>t-test (p value)</i>		(0.0248)				(0.1214)				(0.0048)								
<i>Wilcoxon (p value)</i>		(0.1409)				(0.0162)				(0.0029)								
<i>Delta</i>	-0.44	0.56	0.25	1.47	-0.21	0.66	0.31	1.64	-2.00	-0.08	-0.00	1.71						
<i>t-test (p value)</i>		(0.0309)				(0.0236)				(0.8226)								
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				(0.3180)								



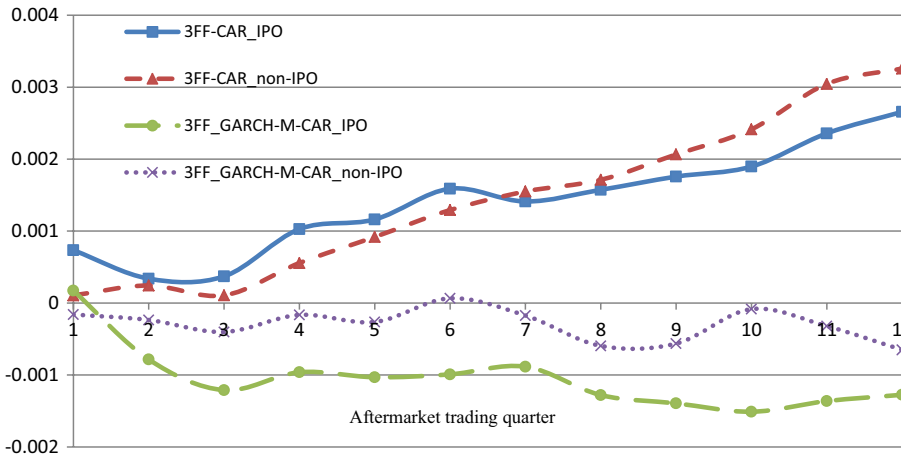
**Table 5** (continued)

Coefficients	IPOs					non-IPOs					DIFF: ( $\alpha_{IPO} - \alpha_{non-IPO}$ )					
	25%	MEAN	MED	75%	25%	MEAN	MED	75%	25%	MEAN	MED	75%	25%	MEAN	MED	75%
<i>Arch0</i>	$0.05 \times 10^{-3}$	$0.72 \times 10^{-3}$	$0.23 \times 10^{-3}$	$0.67 \times 10^{-3}$	$0.05 \times 10^{-3}$	$0.71 \times 10^{-3}$	$0.16 \times 10^{-3}$	$0.56 \times 10^{-3}$	$-0.27 \times 10^{-3}$	$0.03 \times 10^{-3}$	$0.02 \times 10^{-3}$	$0.37 \times 10^{-3}$				
<i>t-test (p value)</i>		(<0.0001)				(<0.0001)					(0.0817)					
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)					(0.0091)					
<i>Arch1</i>	0.06	0.23	0.15	0.28	0.08	0.27	0.18	0.23	-0.18	-0.03	-0.02	0.13				
<i>t-test (p value)</i>		(<0.0001)				(<0.0001)					(0.1107)					
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)					(0.0363)					
<i>Garch1</i>	0.09	0.50	0.57	0.82	0.05	0.47	0.56	0.78	-0.24	0.04	0.00	0.35				
<i>t-test (p value)</i>		(<0.0001)				(<0.0001)					(0.0286)					
<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)					(0.0273)					
<i>N</i>																

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This table reports the mean, the median and the quartiles of the coefficients estimated from the modified three-factor (3FF) model with a GARCH-M extension (see Eqs. 2 and 3), for individual IPOs and matched non-IPOs' equities during the first 3 years of IPO trading. This model is estimated for IPO and matched non-IPO individual stocks during the first 3 years of IPO trading.  $\beta_{MKT}$ ,  $\beta_{SMB}$ , and  $\beta_{HML}$  are the respective sensitivities of the individual expected returns to the market ( $R_{m,t} - R_{f,t}$ ), size (SMB) and book-to-market (HML) factors. The "Delta" coefficient ( $\delta$ ) measures the sensitivity of the individual expected returns to the conditional idiosyncratic volatility. The intercept ( $\alpha^{F.E.GARCH-M}$ ) is adjusted for systematic risk factors (market, size, and book-to-market) as well as firm-level idiosyncratic risk. The coefficients ( $\gamma$ ,  $\theta$  and  $\eta$ ) relative to the variance Eq. (3) are constrained to be positive to ensure positive variance. The coefficient  $\gamma$  corresponds to the intercept in the variance Eq. (3). The coefficient  $\theta$  is associated with the previous period squared residual. The coefficient  $\eta$  is associated with the last period forecast of variance. The non-IPOs equities are selected based on industry, sales, profitability and growth similar to those of the IPOs equities using the propensity score matching method. The Wilcoxon signed rank test is presented as a non-parametric alternative to a t-test when the observations cannot be assumed normally distributed. The one-sample t-test (Wilcoxon signed rank test) is used to determine whether the mean (median) of the sample is equal to zero ( $H_0: \mu = 0$ ). The two sample t-test is used to compare the difference between two means to zero ( $H_0: \mu \text{ of the difference} = 0$ ). The Wilcoxon signed-rank test for two samples is used to test the null hypothesis that the two distributions are identical against the alternative hypothesis that the two distributions differ only with respect to their median. Values in parentheses correspond to the  $p$  values of t-test and Wilcoxon signed rank test



**Fig. 1** Cumulative abnormal aftermarket returns over the first 3 years of IPO trading: IPOs versus non-IPOs. This figure reports the standard and modified 3FF (median) cumulative abnormal return CAR series over the first 12 quarters of IPO trading for both IPOs and matched non-IPOs equities. The non-IPOs equities are selected based on industry, sales, profitability and growth similar to those of the IPOs equities using the propensity score matching method. The cumulative abnormal return CAR is measured on the median of alphas from the standard and modified 3FF (with GARCH-M extension) models in each quarter

respectively) and their peers (−0.42 and −0.11, respectively).<sup>19</sup> We recognize that the standard 3FF model, which leads to positive and significant intercepts for both IPOs and matched non-IPO equities, misrepresents abnormal returns because it does not account for a firm-level risk premium.

Besides, we find that the difference in intercepts from the modified 3FF model between each IPO and its peer is not statistically significant, suggesting that IPOs do not significantly underperform matched firm in the long run.

Figure 1 shows an illustration of the standard and modified 3FF (median) cumulative abnormal return (CAR)<sup>20</sup> series over the first 12 quarters of IPO trading for both IPO and non-IPO equities. This figure reveals that the modified 3FF-CARs are lower than the returns computed from the standard 3FF model for both equities (IPOs and matched non-IPOs). The standard 3FF model shows a better performance for IPOs than their peers during six quarters after the offer date that may be due to the stabilization practices of underwriters and the lock-up period.<sup>21</sup> However, the modified 3FF model shows that IPOs outperform their peers only during the first quarter of IPO trading. Afterward, we note that IPOs underperform their peers for the rest of the period.

It seems that the modified 3FF model can detect the negative effect of the end of the lock-up period on IPO CARs, while the standard 3FF model still produces higher CARs for IPOs compared to their peers even after the end of the period. Unlike the standard 3FF, the

<sup>19</sup> The *p* value of the Wilcoxon test indicates that only the alpha for non-IPOs is significantly negative.

<sup>20</sup> Cumulative abnormal returns (CARs) are measured with the median of alphas from the standard and modified 3FF models in each quarter.

<sup>21</sup> The lock-up period usually lasts between 90 to 180 days after the offering.

modified 3FF model shows decreasing IPO CARs and yields negative medians. However, the modified 3FF model produces CAR close to zero for matched non-IPO equities.

Furthermore, our findings in Table 5 show that Delta in the modified 3FF with GARCH-M exhibits positive and significant mean and median values for both IPO (0.56 with a  $t$  test  $p$  value of (0.03) and 0.25 with a Wilcoxon  $p$  value of ( $<0.0001$ )) and matched non-IPO (0.66 with a  $t$ -test  $p$  value of (0.02) and 0.30 with a Wilcoxon  $p$  value of ( $<0.0001$ )). Although the IPO deltas take lower values compared with matched non-IPOs, the  $t$ -test and Wilcoxon  $p$  values indicate that the difference in delta between the two samples is insignificant on average. We note significant values for all coefficients ( $\gamma$ ,  $\theta$  and  $\eta$ ) relative to the variance Eq. (3) for the majority of IPOs and matched non-IPO equities, suggesting that the volatility process is time-varying contrarily to the assumption in the standard 3FF model. Results relative to the difference in the intercepts ( $\gamma_{IPOi} - \gamma_{non-IPOi}$ ) of the variance in Eq. (3) indicate that IPOs exhibit greater variances than their peers on average. In addition, it appears that IPOs take higher values of  $\eta$  (the coefficient associated with the last period forecast of variance) than matched non-IPO equities, suggesting that the variance of IPO returns is more persistent than that of their peers.

Besides, results relative to the median difference in  $\theta$  (the coefficient associated with the last period squared residual) between IPOs and non-IPO equities indicate that the variance of non-IPOs' returns is more sensitive to last period news than that of IPO returns.

Overall, the comparison between standard and modified 3FF models using different information criteria<sup>22</sup> leads us to recognize the superiority of the later compared to the former that does not account for time-varying variance and ignores the possible relationship between idiosyncratic risk and expected returns. Hence, we show that it is important to consider not only IPO returns but also the time variation in the issuing firm-level variance when comparing IPOs with their peers. It turns out that when we consider the impact of idiosyncratic risk on expected returns, we find that the average IPO underperformance with respect to their peers disappears. The median value of the alpha coefficients has changed from  $-0.008\%$  with a Wilcoxon  $p$  value of 0.08 (using the standard 3FF model in Table 3) to  $0.009\%$  with a Wilcoxon  $p$  value of 0.52 (using the modified 3FF model in Table 5). We infer that this IPO underperformance is mainly due to model misspecification that considers neither the time-varying volatility process nor the specific firm risk exposure. It seems that a part of the abnormality in the standard measure of abnormal returns could be attributed to a time-varying specific risk premium.

#### 4.4 Idiosyncratic risk variation over event time

Since we assume that standard abnormal returns measures could include a portion associated with a time-varying firm-specific risk premium, we show in this sub-section how idiosyncratic risk varies over time depending on: (1) the type of stock: IPO versus non-IPO and (2) the IPO profile: high versus low-idiosyncratic risk IPOs during the first quarter of IPO trading, young versus mature issuers, overvalued versus undervalued issues, technology versus non-technology IPOs and firms going public in hot, quiet or crisis markets. Our

<sup>22</sup> Further details not reported (available for any request) including the R-Squared and some information criteria (the Akaike's Information Criteria (AIC), the corrected Akaike's Information Criteria (AICC) and the Bayesian Information Criteria (BIC) indicate that the modified 3FF model with GARCH-M fits the data better.

purpose is to find characteristics that predict the biggest change in stocks idiosyncratic risk over the first 3 years of IPO trading, which could affect IPO long-run performance.

Figure 2 reports the median daily conditional idiosyncratic variance for IPOs and their matched firms computed on the basis of the modified 3FF model with GARCH-M during the first 3 years of IPO trading. This figure shows that the IPO conditional idiosyncratic risk (CIV) exhibits a downward trend over the IPO event time. However, the conditional idiosyncratic risk for comparable non-IPO equities is lower and seems less variable over the IPO event time. Figure 2 also shows that the difference in the idiosyncratic risk components between issuing and matched non-issuing firms is large in the early aftermarket stage and becomes smaller towards the end of the third year of the offer. We infer that the problem of asymmetric information is more important in IPO stocks than for non-IPO ones. Nevertheless, as the market provides more information about the new issue over time, the level of IPO idiosyncratic risk tends to decrease, approaching the idiosyncratic risk level of its comparable firm.

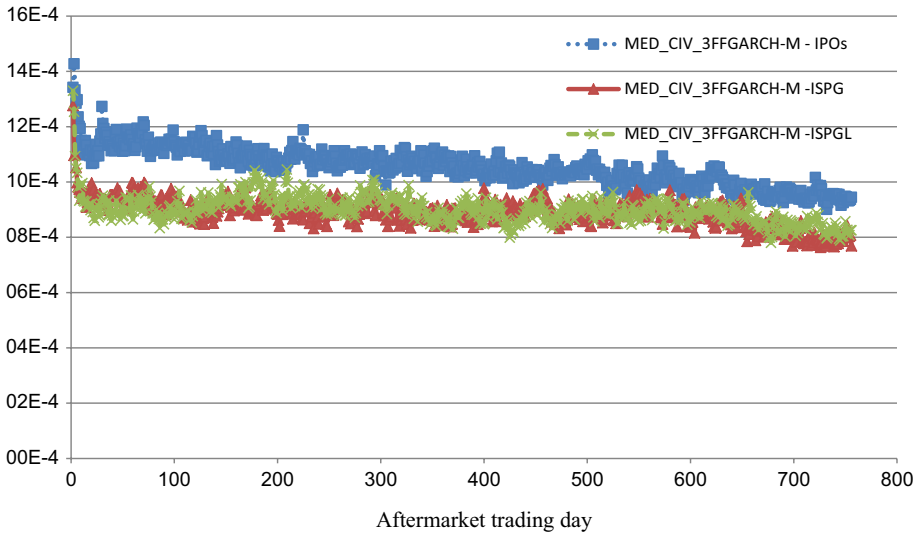
We present in Fig. 3 the time variation in the realized idiosyncratic variance (RIV) over the first 12 quarters of the offering depending on issue characteristics commonly used in the IPO literature (Ritter 1991) and mainly related to the firm risk level, namely the maturity of the issuing firm, the pre-IPO valuation, the industry, and the period of issuance.

Figure 3 (Panel A) shows the long-run time variation in idiosyncratic risk according to the risk characteristics of the IPO during the early aftermarket stage. We split our IPO sample into two portfolios based on their level of idiosyncratic risk in the first quarter of IPO trading: (1) high idiosyncratic-risk IPOs that exhibit an idiosyncratic risk level above the median and (2) low idiosyncratic-risk IPOs that exhibit an idiosyncratic risk level below the median. We note that IPOs characterized by a high level of idiosyncratic risk in the first quarter of IPO trading continue to exhibit high idiosyncratic risk during the next 11 quarters. We also show that idiosyncratic risk associated with high idiosyncratic-risk IPOs exhibit a downward trend over time and tend to reach the level of idiosyncratic risks associated with low idiosyncratic-risk IPOs.

Figure 3 (Panel B) shows the time variation in idiosyncratic risk for young versus mature listings.<sup>23</sup> We note higher idiosyncratic risk over the first 12 quarters for young IPOs. This finding is consistent with Fink et al. (2010) who show that the maturity of public firms could explain the increase of the idiosyncratic risk in the overall market over calendar time. In addition, we find that both IPO groups (mature and young) exhibit a downward trend in idiosyncratic risk over the first 12 quarters of the offering. However, we note that the slope of the trend is larger for young IPOs. We infer that the young age of the IPOs only accentuates the slope level of the trend in idiosyncratic risk but it is not the cause of this negative trend. When we control for IPO age, the negative trend of the idiosyncratic risk over event time persists for mature IPOs even if the slope is lower than that of young IPOs. Therefore, we could not attribute the negative trend in event-time idiosyncratic risk to the age of the issuing firm.

Figure 3 (Panel C) shows the idiosyncratic risk variation over the event time according to the pre-IPO valuation. We split our IPO sample into two portfolios: (1) undervalued

<sup>23</sup> The age of the issuing firm is determined as follows: the year of the offering minus the year of foundation. Foundation dates are collected from the following website: (<http://bear.warrington.ufl.edu/ritter/foundingdates.htm>). We split our IPO sample sorted by age into quartiles. The first quartile of the sample constitutes the young IPOs. The last quartile constitutes the mature IPOs.



**Fig. 2** Conditional idiosyncratic variance over IPO event time: IPOs versus non-IPOs. This figure reports the median daily conditional idiosyncratic variance (CIV) for IPOs and their matched non-IPO firms (non-IPOs are firms comparable with IPOs according to: (1) Industry/Size/Profitability/Growth (ISPG) and (2) Industry/Size/Profitability/Growth/Leverage (ISPGL)) based on the modified three-factor Fama–French model with GARCH-M (in mean) extension. CIV are calculated for the three first years of IPO trading (from the first day of the IPO event to day 756). CIV are assessed from regressions on individual excess returns for IPOs and non-IPOs firms

IPOs and (2) overvalued IPOs. We use the price-to-value ratio<sup>24</sup> as proposed by Zheng (2007) to distinguish between undervalued and overvalued IPOs. We find that overvalued IPOs exhibit higher idiosyncratic risk than undervalued IPOs. In addition, the downward trend in idiosyncratic risk is greater (in absolute value) for overvalued IPOs than for undervalued IPOs. We also show that the magnitude of the difference in the idiosyncratic risk between overvalued and undervalued IPOs is larger during the early aftermarket stage.

In Fig. 3 (Panel D), we check how firm-level idiosyncratic risk varies over event time for five IPO portfolios sorted by industry.<sup>25</sup> We show that HITEC IPOs exhibit the highest idiosyncratic risk, which tends to decrease over the IPO event time. This finding is consistent with Lowry et al. (2010) who note that technology issues are riskier. This result allows

<sup>24</sup> The pre-IPO valuation is approximated by the price-to-value ratio as computed by Zheng (2007) as follows:

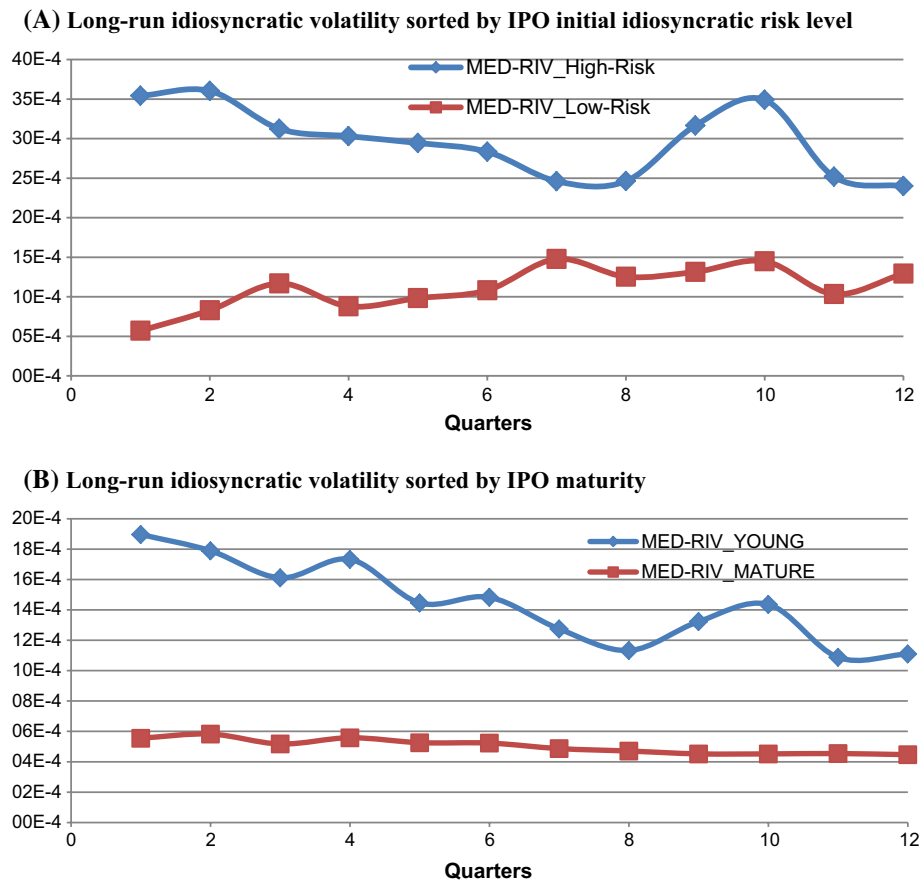
$$\left(\frac{P}{V}\right)_{EBITDA}^Z = \frac{\left[\frac{\text{OfferPrice} \times (\text{CRSPSharesOutstanding} - \text{NewPrimaryShares}) - \text{Cash} + \text{TotalDebt}}{\text{EBITDA}(\text{PriorOfferingQuarter})}\right]_{IPO}}{\left[\frac{\text{MarketPrice}(\text{OneDayPriortheIPOOfferDate}) \times \text{CRSPSharesOutstanding} - \text{Cash} + \text{TotalDebt}}{\text{EBITDA}(\text{PriorOfferingQuarter})}\right]_{Match}}$$

If the price-to-value ratio is greater (smaller) than one, then the IPO offer price is higher (lower) than the fair value of the issue and classified as overvalued (undervalued) by the underwriter.

<sup>25</sup> We split our IPO (and matched non-IPO) sample into five portfolios on the basis of the firm industry: (1) CNMR includes sustainable and unsustainable consumption, wholesale, retail, and some services (laundries, repair shops); (2) MANUF includes manufacturing, energy, and utilities; (3) HITEC includes business facilities, telephone, and television transmission; (4) HLTH includes healthcare, medical equipment, and medicines; and (5) OTHER includes mining, construction, transportation, hotels, services, entertainment, and the financial sector.

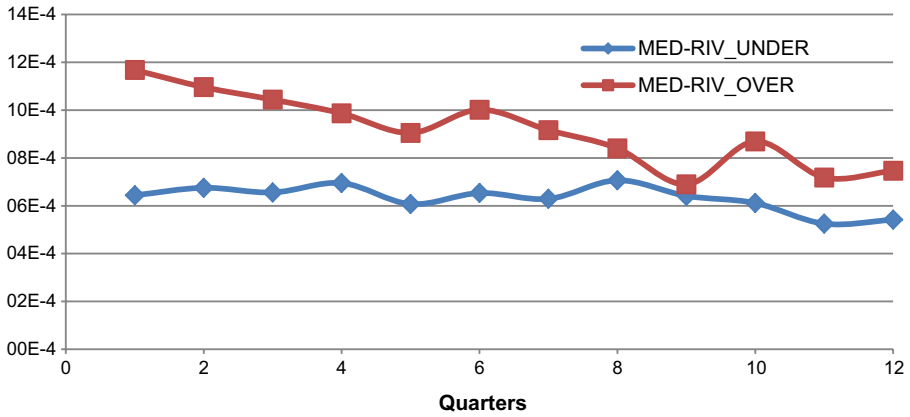
us to infer that the degree of information asymmetry is higher for IPOs in the high-tech industry.

Figure 3 (Panel E) shows how firm-level idiosyncratic risk varies over IPO event time depending on the IPO's issuance period. We note that firms that went public in 2000 are characterized by the highest idiosyncratic risk over the IPO event time (12 first quarters of the offering). Many risky firms choose to go public in a hot-issue market because it is easier to market their issue without leaving money on the table (Beaulieu and Mrissa Bouden 2015a). However, it seems that IPOs in the crisis sub-period exhibit a lower level of idiosyncratic risk because high-idiosyncratic risk firms keep away from going public in a period of crisis to avoid being constrained to leave large amounts of money on the table. Moreover, we note that the idiosyncratic risk of hot market IPOs tends to decrease over

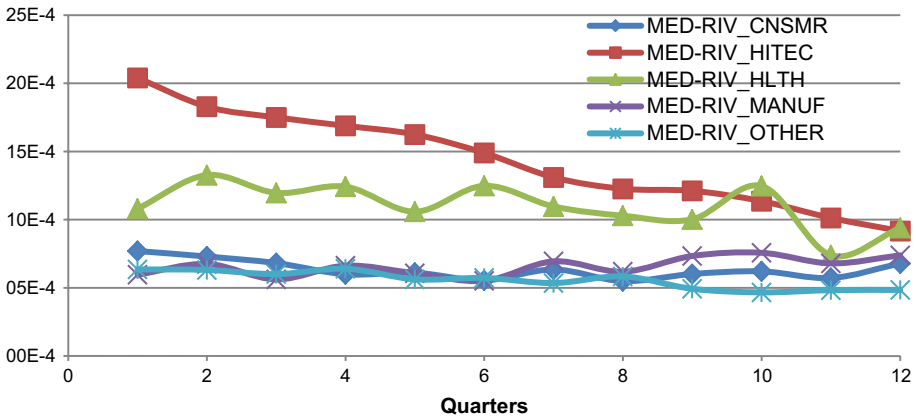


**Fig. 3** Time variation in the idiosyncratic volatility over the 12 first quarters of offering depending on IPO profile. These figures report the time variation of the median of the idiosyncratic volatility over the first 3 years of IPO trading for high idiosyncratic-risk versus low idiosyncratic-risk IPOs' portfolios (Panel A), young versus mature issuing firms (Panel B), undervalued versus overvalued IPOs' portfolios (Panel C), IPOs depending on their industry (Panel D) and IPOs depending on their issuance (hot/quiet/crisis) period (Panel E). The realized idiosyncratic (RIV) volatilities are computed from the three factors model of Fama and French (1993) over the 12 first quarters of IPO trading

**(C) Long-run idiosyncratic volatility sorted by pre-IPO valuation**



**(D) Long-run idiosyncratic volatility sorted by IPO industry**



**(E) Long-run idiosyncratic volatility sorted by the IPO issuance period**

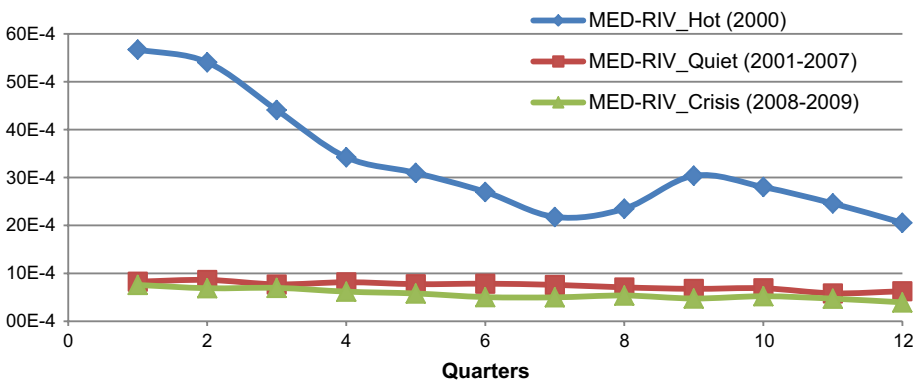


Fig. 3 (continued)

time (with a large negative slope trend). However, the idiosyncratic risk of issues in quiet and crisis sub-periods exhibits a slight downward trend.

In sum, we show that issuing firms exhibit higher idiosyncratic risk than their matched non-IPO firms. Moreover, young IPOs, overvalued IPOs, technology firms and hot-market issues have the highest levels of idiosyncratic risk especially during the early aftermarket stage. Nevertheless, the idiosyncratic risk of these types of IPOs gradually decreases over time becoming indistinguishable from that of matched non-IPO firms.

Chen and Petkova (2012, p. 2745) note that “Portfolios with high (low) idiosyncratic volatility relative to the Fama–French (1993) model have positive (negative) exposures to innovations in average stock variance and therefore lower (higher) expected returns”. Based on Chen and Petkova (2012), we expect IPOs with the following characteristics: high idiosyncratic-risk IPOs during the early aftermarket stage, young IPOs, overvalued IPOs, technology firms and hot-market issues, exhibiting the highest levels of idiosyncratic volatility during the first 3 years of IPO trading, to have positive exposure to the idiosyncratic volatility as well as lower long-run returns.

#### 4.5 Long-run performance and idiosyncratic risk exposure according to the IPO profile

This subsection focuses on IPO long-run performance and IPO idiosyncratic risk exposure controlling for different characteristics of the issues (firm risk level, maturity of the issuing firm, pre-IPO valuation, the industry, and the period of issuance). We aim to examine how firm-level idiosyncratic risk affects long-run returns.

Table 6 reports results for the distribution of the intercepts (Panel A) and the sum of the beta coefficients<sup>26</sup> (Panel B) from the standard versus the modified 3FF (with GARCH-M (in mean) extension) models for the following IPO portfolios: (1) high idiosyncratic-risk versus low idiosyncratic-risk IPOs, (2) young versus mature IPOs, (3) overvalued versus undervalued IPOs, (3) technology IPOs versus others, and (4) IPOs going public in hot versus quiet versus crisis periods. Table 6 also shows the distribution of the Delta<sup>27</sup> (Panel C) coefficient that measures idiosyncratic risk exposure resulting from the estimation of Eqs. (2) and (3) of the modified 3FF model depending on the IPO profile.

Panel (A) of Table 6 shows that 3FF intercepts change signs for some types of IPOs when we account for the premium on the idiosyncratic risk in the modified 3FF model with GARCH-M. We note that new intercepts associated with high idiosyncratic-risk IPOs,<sup>28</sup> technology issues, and hot IPOs become significantly negative,<sup>29</sup> suggesting that these types of IPOs underperform the market in the long run.

In addition, our results show that the differences in intercepts between high idiosyncratic-risk and low idiosyncratic-risk IPOs, HITEC and others, and issues in hot and quiet

<sup>26</sup> The sum of the beta coefficients:  $Betas = Beta_{MKT} + Beta_{SMB} + Beta_{HML}$ , presents the sensitivity of IPO event-time individual returns to systematic risk factors (market, size and book-to-market).

<sup>27</sup> The “Delta” coefficient ( $\delta_i$ ) is computed from the modified 3FF model with GARCH-M and presents the sensitivity of event-time IPO individual returns to idiosyncratic volatility.

<sup>28</sup> Other findings (not reported) show that high idiosyncratic-risk IPOs exhibit more negative abnormal returns (−0.047%) than their peers in the same risk category (−0.014%). The difference between the two groups of stocks (IPOs and non-IPOs) in the same category of risk is statistically significant.

<sup>29</sup> The new intercept associated with overvalued IPOs also becomes negative, but not statistically significant.



**Table 6** The “Alpha”, “Betas” and “Delta” Distributions depending on IPO profile

IPO Profile	Portfolios	Alpha Distribution					Modified 3FF						
		Standard 3FF		75%			25%		75%				
		25%	MEAN	MED	75%	25%	MEAN	MED	75%	25%	MEAN	MED	75%
<i>Panel (A): The “Alpha” Distribution depending on IPO profile</i>													
Idiosyncratic risk level	HIGH-RISK	$-0.73 \times 10^{-3}$	$0.28 \times 10^{-3}$	$0.43 \times 10^{-3}$	$1.24 \times 10^{-3}$	$-3.26 \times 10^{-3}$	$0.16 \times 10^{-3}$	$-0.47 \times 10^{-3}$	$1.52 \times 10^{-3}$				
	<i>t</i> -test ( <i>p</i> value)		(0.0036)					(0.2154)					
	Wilcoxon ( <i>p</i> value)		(0.0003)					(0.0055)					
	<i>N</i>					285							
	LOW-RISK	$-0.22 \times 10^{-3}$	$0.29 \times 10^{-3}$	$0.38 \times 10^{-3}$	$0.97 \times 10^{-3}$	$-1.12 \times 10^{-3}$	$-0.45 \times 10^{-3}$	$0.20 \times 10^{-3}$	$1.42 \times 10^{-3}$				
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)					(0.2343)					
	Wilcoxon ( <i>p</i> value)		(<0.0001)					(0.2306)					
	<i>N</i>					286							
	HIGH versus LOW												
	Z		0.2590					-2.8012					
	(Pr > Z)		(0.3978)					(0.0025)					
	(Pr >  Z )		(0.7956)					(0.0051)					
	Chi-2		0.0672					7.8481					
	(Pr > Chi-2)		(0.7954)					(0.0051)					

**Table 6** (continued)

IPO Profile	Portfolios	Alpha Distribution							
		Standard 3FF		Modified 3FF					
		25%	MEAN	MED	75%	25%	MEAN	MED	75%
Maturity	YOUNG	$-0.54 \times 10^{-3}$	$0.32 \times 10^{-3}$	$0.52 \times 10^{-3}$	$1.30 \times 10^{-3}$	$-2.66 \times 10^{-3}$	$0.60 \times 10^{-3}$	$-0.06 \times 10^{-3}$	$1.68 \times 10^{-3}$
	<i>t</i> -test ( <i>p</i> value)		(0.0850)				(0.4045)		
	Wilcoxon ( <i>p</i> value)		(0.0011)				(0.3692)		
	<i>N</i>				159				
	MATURE	$-0.28 \times 10^{-3}$	$0.32 \times 10^{-3}$	$0.42 \times 10^{-3}$	$0.95 \times 10^{-3}$	$-1.17 \times 10^{-3}$	$0.09 \times 10^{-3}$	$-0.01 \times 10^{-3}$	$1.09 \times 10^{-3}$
	<i>t</i> -test ( <i>p</i> value)		(0.0010)				(0.7157)		
	Wilcoxon ( <i>p</i> value)		(0.0003)				(0.9738)		
	<i>N</i>				116				
	YOUNG versus MATURE								
	Z		-0.5166				0.5489		
(Pr > Z)		(0.3027)				(0.2915)			
(Pr >  Z )		(0.6054)				(0.5831)			
Chi-2		0.2677				0.3021			
(Pr > Chi-2)		(0.6049)				(0.5826)			

Table 6 (continued)

IPO Profile	Portfolios	Alpha Distribution									
		Standard 3FF					Modified 3FF				
		25%	MEAN	MED	75%	25%	MEAN	MED	75%		
Pre-IPO valuation	OVER	$-0.73 \times 10^{-3}$	$0.04 \times 10^{-3}$	$0.27 \times 10^{-3}$	$0.96 \times 10^{-3}$	$-1.82 \times 10^{-3}$	$-0.31 \times 10^{-3}$	$-0.15 \times 10^{-3}$	$1.44 \times 10^{-3}$		
	<i>t</i> -test ( <i>p</i> value)		(0.7112)					(0.4800)			
	Wilcoxon ( <i>p</i> value)		(0.1801)					(0.4653)			
	<i>N</i>					145					
	UNDER	$-0.18 \times 10^{-3}$	$0.49 \times 10^{-3}$	$0.47 \times 10^{-3}$	$1.20 \times 10^{-3}$	$-1.73 \times 10^{-3}$	$0.42 \times 10^{-3}$	$0.21 \times 10^{-3}$	$1.44 \times 10^{-3}$		
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)					(0.3541)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)					(0.8561)			
	<i>N</i>					181					
	OVER versus UNDER										
	<i>Z</i>		-2.4442						-0.6208		
(Pr > Z)		(0.0073)						(0.2674)			
(Pr >  Z )		(0.0145)						(0.5347)			
Chi-2		5.9769						0.3861			
(Pr > Chi-2)		(0.0145)						(0.5343)			

**Table 6** (continued)

IPO Profile	Portfolios	Alpha Distribution									
		Standard 3FF					Modified 3FF				
		25%	MEAN	MED	75%	75%	25%	MEAN	MED	75%	75%
Industry	HITEC	$-0.73 \times 10^{-3}$	$0.33 \times 10^{-3}$	$0.50 \times 10^{-3}$	$1.33 \times 10^{-3}$	$1.33 \times 10^{-3}$	$-2.81 \times 10^{-3}$	$0.88 \times 10^{-3}$	$-0.39 \times 10^{-3}$		$1.35 \times 10^{-3}$
	<i>t</i> -test ( <i>p</i> value)		(0.0085)						(0.2180)		
	Wilcoxon ( <i>p</i> value)		(0.0050)						(0.0400)		
	<i>N</i>					198					
	OTHERS	$-0.29 \times 10^{-3}$	$0.26 \times 10^{-3}$	$0.34 \times 10^{-3}$	$0.93 \times 10^{-3}$	$0.93 \times 10^{-3}$	$-1.83 \times 10^{-3}$	$-0.31 \times 10^{-3}$	$0.01 \times 10^{-3}$		$1.60 \times 10^{-3}$
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)						(0.3874)		
	Wilcoxon ( <i>p</i> value)		(<0.0001)						(0.8314)		
	<i>N</i>					373					
	HITEC versus OTHERS										
	Z		1.2224							-1.6770	
(Pr > Z)		(0.1108)							(0.0468)		
(Pr >  Z )		(0.2216)							(0.0935)		
Chi-2		1.4249							2.8132		
(Pr > Chi-2)		(0.2215)							(0.0935)		

Table 6 (continued)

IPO Profile	Portfolios	Alpha Distribution									
		Standard 3FF					Modified 3FF				
		25%	MEAN	MED	75%	25%	MEAN	MED	75%	75%	
Issuance period	HOT	$-0.96 \times 10^{-3}$	$0.16 \times 10^{-3}$	$0.25 \times 10^{-3}$	$1.23 \times 10^{-3}$	$-5.30 \times 10^{-3}$	$-1.72 \times 10^{-3}$	$-1.22 \times 10^{-3}$	$1.01 \times 10^{-3}$		
	<i>t</i> -test ( <i>p</i> value)		(0.4172)					(0.0343)			
	Wilcoxon ( <i>p</i> value)		(0.3024)					(0.0002)			
	<i>N</i>					108					
	QUIET	$-0.33 \times 10^{-3}$	$0.32 \times 10^{-3}$	$0.43 \times 10^{-3}$	$1.09 \times 10^{-3}$	$-1.62 \times 10^{-3}$	$1.18 \times 10^{-3}$	$0.29 \times 10^{-3}$	$1.52 \times 10^{-3}$		
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)					(0.2115)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)					(0.9576)			
	<i>N</i>					423					
	CRISIS	$-0.10 \times 10^{-3}$	$0.22 \times 10^{-3}$	$0.21 \times 10^{-3}$	$0.66 \times 10^{-3}$	$-0.32 \times 10^{-3}$	$1.05 \times 10^{-3}$	$0.53 \times 10^{-3}$	$1.53 \times 10^{-3}$		
	<i>t</i> -test ( <i>p</i> value)		(0.1704)					(0.1141)			
Wilcoxon ( <i>p</i> value)		(0.0689)					(0.0355)				
<i>N</i>					40						
HOT versus QUIET	HOT versus QUIET										
	<i>Z</i>		-1.0944					-3.8763			
	(Pr > Z)		(0.1369)					(<0.0001)			
	(Pr >  Z )		(0.2738)					(<0.0001)			
	Chi-2		1.1985					15.0284			
	(Pr > Chi-2)		(0.2736)					(0.0001)			
	CRISIS versus QUIET										
	<i>Z</i>		-0.9291					1.4545			
	(Pr > Z)		(0.1764)					(0.0729)			
	(Pr >  Z )		(0.3528)					(0.1458)			
Chi-2		0.8644					2.1175				
(Pr > Chi-2)		(0.3525)					(0.1456)				

**Table 6** (continued)

IPO Profile	Portfolios	Betas Distribution									
		Standard 3FF					Modified 3FF				
		25%	MEAN	MED	75%	N	25%	MEAN	MED	75%	N
<i>Panel (B): The “Betas” Distribution depending on IPO profile</i>											
Idiosyncratic risk level	HIGH-RISK	0.92	1.83	1.80	2.66		0.71	1.69	1.70		2.46
	<i>t-test (p value)</i>		(<0.0001)					(<0.0001)			
	<i>Wilcoxon (p value)</i>		(<0.0001)					(<0.0001)			
	<i>N</i>					285					
Idiosyncratic risk level	LOW-RISK	0.77	1.48	1.44	2.05		0.75	1.39	1.38		1.98
	<i>t-test (p value)</i>		(<0.0001)					(<0.0001)			
	<i>Wilcoxon (p value)</i>		(<0.0001)					(<0.0001)			
	<i>N</i>					286					
Idiosyncratic risk level	HIGH versus LOW										
	<i>Z</i>		3.8848					3.2071			
	<i>(Pr &gt; Z)</i>		(<0.0001)					(0.0007)			
	<i>(Pr &gt;  Z )</i>		(0.0001)					(0.0013)			
Idiosyncratic risk level	Chi-2		15.0940					10.2869			
	<i>(Pr &gt; Chi-2)</i>		(0.0001)					(0.0013)			

Table 6 (continued)

IPO Profile	Portfolios	Betas Distribution							
		Standard 3FF			Modified 3FF				
		25%	MEAN	MED	75%	25%	MEAN	MED	75%
Maturity	YOUNG	0.80	1.70	1.73	2.52	0.67	1.59	1.68	2.41
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	Wilcoxon ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	<i>N</i>				159				
	MATURE	0.95	1.70	1.50	2.41	0.91	1.58	1.50	2.17
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	Wilcoxon ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	<i>N</i>				116				
	YOUNG versus MATURE								
	<i>Z</i>		-0.4752				-0.2971		
(Pr > <i>Z</i> )		(0.3173)				(0.3832)			
(Pr >   <i>Z</i>  )		(0.6347)				(0.7664)			
Chi-2		0.2265				0.0887			
(Pr > Chi-2)		(0.6341)				(0.7658)			

**Table 6** (continued)

IPO Profile	Portfolios	Betas Distribution							
		Standard 3FF			Modified 3FF				
		25%	MEAN	MED	75%	25%	MEAN	MED	75%
Pre-IPO valuation	OVER	0.83	1.61	1.48	2.16	0.75	1.51	1.42	2.10
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	Wilcoxon ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	<i>N</i>					145			
	UNDER	0.90	1.72	1.71	2.44	0.94	1.61	1.69	2.33
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	Wilcoxon ( <i>p</i> value)		(<0.0001)				(<0.0001)		
	<i>N</i>					181			
	OVER versus UNDER								
	<i>Z</i>			-1.2404				-1.4746	
(Pr > <i>Z</i> )			(0.1074)				(0.0702)		
(Pr >   <i>Z</i>  )			(0.2148)				(0.1403)		
Chi-2			1.5401				2.1760		
(Pr > Chi-2)			(0.2146)				(0.1402)		



Table 6 (continued)

IPO Profile	Portfolios	Betas Distribution									
		Standard 3FF					Modified 3FF				
		25%	MEAN	MED	75%	25%	MEAN	MED	75%		
Industry	HITEC	0.93	1.76	1.73	2.53	0.76	1.67	1.61	2.42		
	<i>t-test (p value)</i>		(<0.0001)				(<0.0001)				
	<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				
	<i>N</i>				198						
	OTHERS	0.83	1.60	1.54	2.26	0.73	1.47	1.47	2.15		
	<i>t-test (p value)</i>		(<0.0001)				(<0.0001)				
	<i>Wilcoxon (p value)</i>		(<0.0001)				(<0.0001)				
	<i>N</i>				373						
	HITEC versus OTHERS										
	<i>Z</i>		1.9216				1.6264				
	(Pr > Z)		(0.0273)				(0.0519)				
	(Pr >  Z )		(0.0547)				(0.1039)				
	Chi-2		3.6937				2.6459				
	(Pr > Chi-2)		(0.0546)				(0.1038)				

**Table 6** (continued)

IPO Profile	Portfolios	Betas Distribution									
		Standard 3FF					Modified 3FF				
		25%	MEAN	MED	75%	75%	25%	MEAN	MED	75%	75%
Issuance period	HOT	0.89	2.13	2.29	3.39	3.39	0.59	1.87	1.86	3.19	
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)					(<0.0001)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)					(<0.0001)			
	<i>N</i>					108					
	QUIET	0.86	1.57	1.55	2.19	2.19	0.76	1.49	1.51	2.15	
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)					(<0.0001)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)					(<0.0001)			
	<i>N</i>					423					
	CRISIS	0.84	1.24	1.25	1.74	1.74	0.89	1.24	1.28	1.64	
	<i>t</i> -test ( <i>p</i> value)		(<0.0001)					(<0.0001)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)					(<0.0001)			
	<i>N</i>					40					
HOT versus QUIET											
<i>Z</i>		4.2508					2.3065				
(Pr > Z)		(<0.0001)					(0.0105)				
(Pr >  Z )		(<0.0001)					(0.0211)				
Chi-2		18.0724					5.3217				
(Pr > Chi-2)		(<0.0001)					(0.0211)				
CRISIS versus QUIET											
<i>Z</i>		-2.0096					-1.6561				
(Pr > Z)		(0.0222)					(0.0489)				
(Pr >  Z )		(0.0445)					(0.0977)				
Chi-2		4.0411					2.7446				
(Pr > Chi-2)		(0.0444)					(0.0976)				

**Table 6** (continued)

IPO Profile	Portfolios	Delta Distribution				
		Modified 3FF	MEAN	MED	75%	
Idiosyncratic risk level	HIGH-RISK	-0.24	0.44	0.40	1.45	
	<i>t</i> -test ( <i>p</i> value)		(0.0538)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)			
	<i>N</i>		285			
	LOW-RISK	-0.69	0.69	0.04	1.48	
	<i>t</i> -test ( <i>p</i> value)		(0.0737)			
	Wilcoxon ( <i>p</i> value)		(0.0024)			
	<i>N</i>		286			
	HIGH versus LOW					
	<i>Z</i>		1.1783			
(Pr > <i>Z</i> )		(0.1193)				
(Pr >   <i>Z</i>  )		(0.2387)				
Chi-2		1.3889				
(Pr > Chi-2)		(0.2386)				

**Table 6** (continued)

IPO Profile	Portfolios	Delta Distribution				
		Modified 3FF	MEAN	MED	75%	
Maturity	YOUNG	-0.50	1.08	0.31	1.40	
	<i>t</i> -test ( <i>p</i> value)		(0.0750)			
	Wilcoxon ( <i>p</i> value)		(0.0021)			
	<i>N</i>		159			
	MATURE	-0.04	0.44	0.28	1.78	
	<i>t</i> -test ( <i>p</i> value)		(0.1043)			
	Wilcoxon ( <i>p</i> value)		(0.0002)			
	<i>N</i>		116			
	YOUNG versus MATURE					
	<i>Z</i>		0.8084			
	(Pr > <i>Z</i> )		(0.2094)			
	(Pr >   <i>Z</i>  )		(0.4189)			
Chi-2		0.6547				
(Pr > Chi-2)		(0.4184)				

Table 6 (continued)

IPO Profile	Portfolios	Delta Distribution				
		Modified 3FF				
		25%	MEAN	MED	75%	
Pre-IPO valuation	OVER	-0.92	0.08	0.02	1.37	
	<i>t</i> -test ( <i>p</i> value)		(0.8424)			
	Wilcoxon ( <i>p</i> value)		(0.1750)			
	<i>N</i>		145			
	UNDER	-0.46	0.81	0.44	1.82	
	<i>t</i> -test ( <i>p</i> value)		(0.0949)			
	Wilcoxon ( <i>p</i> value)		(0.0001)			
	<i>N</i>		181			
	OVER versus UNDER					
	<i>Z</i>		-1.7193			
(Pr > <i>Z</i> )		(0.0428)				
(Pr >   <i>Z</i>  )		(0.0856)				
Chi-2		2.9581				
(Pr > Chi-2)		(0.0854)				

**Table 6** (continued)

IPO Profile	Portfolios	Delta Distribution				
		25%	MEAN	MED	75%	
Industry						
	HITEC	-0.24	0.68	0.39	1.34	
	<i>t</i> -test ( <i>p</i> value)		(0.0136)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)			
	<i>N</i>		198			
	OTHERS	-0.51	0.51	0.17	1.63	
	<i>t</i> -test ( <i>p</i> value)		(0.1002)			
	Wilcoxon ( <i>p</i> value)		(<0.0001)			
	<i>N</i>		373			
	HITEC versus OTHERS					
	<i>Z</i>		0.5647			
	(Pr > <i>Z</i> )		(0.2861)			
	(Pr >   <i>Z</i>  )		(0.5723)			
	Chi-2		0.3192			
	(Pr > Chi-2)		(0.5791)			

**Table 6** (continued)

IPO Profile	Portfolios	Delta Distribution				
		Modified 3FF				
		25%	MEAN	MED	75%	
Issuance period	HOT	0.00	0.71	0.60	1.34	
	<i>t</i> -test ( <i>p</i> value)			(<0.0001)		
	Wilcoxon ( <i>p</i> value)			(<0.0001)		
	<i>N</i>		108			
	QUIET	-0.61	0.68	0.14	1.63	
	<i>t</i> -test ( <i>p</i> value)			(0.0211)		
	Wilcoxon ( <i>p</i> value)			(<0.0001)		
	<i>N</i>		423			
	CRISIS	-1.24	-0.13	0.00	0.99	
	<i>t</i> -test ( <i>p</i> value)			(0.2550)		
	Wilcoxon ( <i>p</i> value)			(0.6157)		
	<i>N</i>		40			
HOT versus QUIET	HOT versus QUIET					
	<i>Z</i>		1.7690			
	(Pr> <i>Z</i> )		(0.0384)			
	(Pr>  <i>Z</i>  )		(0.0769)			
	Chi-2		3.1305			
	(Pr> Chi-2)		(0.0768)			
	CRISIS versus QUIET					
	<i>Z</i>		-1.8168			
	(Pr> <i>Z</i> )		(0.0346)			
	(Pr>  <i>Z</i>  )		(0.0693)			
	Chi-2		3.3029			
	(Pr> Chi-2)		(0.0692)			

**Table 6** (continued)

(Panel A) This table reports the distribution of the intercepts from the standard  $\alpha_i^{FF}$  (see Eq. 1) and modified  $\alpha_i^{FF-GARCH-M}$  (see Eq. 2) three-factor model for the IPO event-time individual returns depending on IPO profile during the first 3 year of IPO trading

(Panel B) This table reports the distribution of the “Betas” ( $Betas = Beta_{MKT} + Beta_{SMB} + Beta_{HML}$ ) from the standard (see Eq. 1) and modified (see Eq. 2) three-factor model for the IPO event-time individual returns depending on IPO profile during the first 3 year of IPO trading

(Panel C) This table reports the distribution of the “Delta” from the modified three-factor model (see Eq. 2) for the IPO event-time individual returns depending on IPO profile during the first 3 year of IPO trading

These tables report the distribution of the coefficients estimated from the standard and modified three-factor (3FF) model (with GARCH-M (in mean) extension) for the IPO event-time individual 3-year returns depending on IPO profile. Panel (A) shows the “Alpha” distribution. The alpha coefficient from the standard (modified) 3FF measures the long-run performance adjusted from the systematic (and idiosyncratic) risk. Panel (B) shows the “Betas” distribution. “Betas” corresponds to the sensitivity to the systematic risks tied to the three factors of Fama and French (1993). “Betas” is the sum of the beta coefficients associated with market, size and book-to-market factors. Panel (C) shows the “Delta” distribution. The “Delta” coefficient from the modified three-factor (3FF) model (with GARCH-M (in mean) extension) measures the exposure to the idiosyncratic risk. The IPO sample is split each time into two portfolios based on: (1) their level of idiosyncratic risk in the first quarter of IPO trading: high (vs. low) idiosyncratic-risk IPOs that exhibit an initial idiosyncratic risk level above (below) the median, (2) issuing firm maturity: the first (last) quartile of the sample constitutes the young (mature) IPOs, (3) pre-IPO valuation: undervalued versus overvalued IPOs are distinguished on the basis of the price-to-value ratio (see footnote p. 22) as proposed by Zheng (2007), (4) IPO industry: technology (HITEC) versus non-technology (OTHERS) issuing firms and (5) IPO issuance period: hot-issue IPO market in 2000 versus quiet IPO market between 2001 and 2007 versus crisis period from the end of 2007 (the start of the American recession) to 2009. The values between brackets present the  $p$  values of the student and Wilcoxon signed-rank tests. We use the non-parametric Wilcoxon and the Chi-2 tests for the difference between IPOs’ groups. We test the null hypothesis that two groups of IPOs have the same continuous distribution



markets move from null (when we use the standard 3FF model) to significantly negative (when we use the modified 3FF model with GARCH-M). However, the difference in intercepts between overvalued and undervalued IPOs goes from significantly negative (when we use the standard 3FF model) to null (when we use the modified 3FF model with GARCH-M). We also note that intercepts for young and mature IPOs move from significantly positive to null when we add the GARCH-M extension to the standard 3FF model. These results lead us to consider that a part of the abnormality in the traditional measure of abnormal return (the intercept from the standard 3FF model) is due to a time-varying firm-level idiosyncratic risk premium. We infer that regardless of the IPO profile, the inclusion of a firm-level idiosyncratic risk premium causes changes of different magnitudes in abnormal returns and/or the difference in abnormal returns between different categories of IPOs.

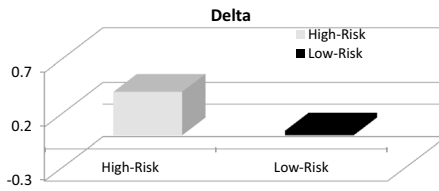
Besides, we note that the “Delta” coefficient, which is our proxy for idiosyncratic risk exposure, is significantly positive for all IPOs except overvalued IPOs and issues in the crisis period that present “Delta” coefficient not significantly different from zero. The results for new issues in the crisis period is expected since the idiosyncratic risk level of the issuers during this period is lower than in hot and quiet markets. However, our results for overvalued IPOs is not consistent with Chen and Petkova (2012) who show that traded firms with high idiosyncratic volatility exhibit positive exposure to this type of risk. In our case, it seems that when investors overvalue a new issue, they are more tolerant towards the specific risk characteristics of the issuer and do not require an additional premium associated with the idiosyncratic risk. Otherwise, the investors who agree to buy overvalued issues are generally uninformed investors. Rock (1986) notes the following adverse selection problem in the IPO allocation process: informed investors only trade for undervalued IPOs, whereas the uninformed investors indiscriminately trade for undervalued and overvalued IPOs. Then, overvalued issues are fully allocated to uninformed investors who do not hold private information about the new issues. Hence, these uninformed investors could not be able to immediately incorporate specific firm risk into prices of overvalued issues, which explains why these specific issues are not exposed to idiosyncratic risk. Therefore, we argue that the difference in abnormal returns between overvalued and undervalued IPOs as well as issues in the crisis and quiet periods is partially attributed to the difference in the idiosyncratic risk exposure.<sup>30</sup>

We suggest that it is not sufficient to look at the time variation in the level of IPO idiosyncratic volatility. Since we assume that IPO idiosyncratic risk exposure plays an important role in IPO long-run performance, we should instead measure the degree of exposure to this type of risk for different categories of IPOs.

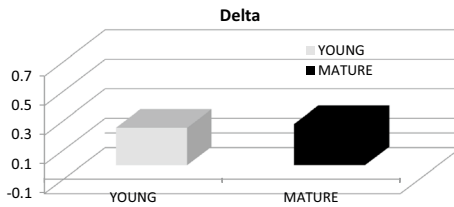
Figure 4 presents the different levels of idiosyncratic risk exposure over the first 3 years of offering, measured by the “Delta” coefficient, according to the issuance period, the industry of the issuing firm, the pre-IPO valuation, the level of IPO idiosyncratic risk during the first quarter of IPO trading and the IPO age. We note that the IPOs most exposed to idiosyncratic risk are mainly the hot-market issues and the undervalued IPOs. High idiosyncratic-risk IPOs and technology issues also present high level of idiosyncratic risk exposure. However, the Wilcoxon test in Panel (C) of Table 6 does not show a significant difference in “Delta” when we compare high idiosyncratic-risk IPOs and technology issues with respectively low idiosyncratic-risk IPOs and issues from other industries.

<sup>30</sup> The non-parametric Wilcoxon test shows that the difference in “Delta” between overvalued and undervalued IPOs as well as issues in crisis and quiet periods is significant.

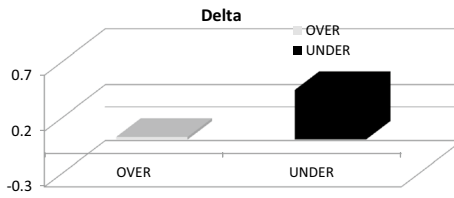
**(A) Idiosyncratic risk exposure sorted by IPO initial idiosyncratic risk level**



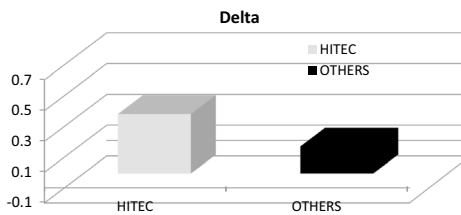
**(B) Idiosyncratic risk exposure sorted by IPO maturity**



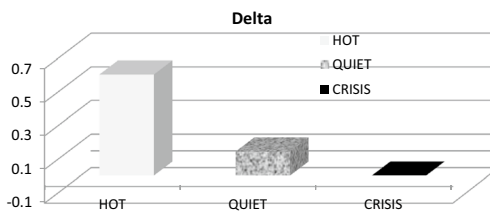
**(C) Idiosyncratic risk exposure sorted by pre-IPO valuation**



**(D) Idiosyncratic risk exposure sorted by IPO industry**



**(E) Idiosyncratic risk exposure sorted by issuance period**



**Fig. 4** Idiosyncratic risk exposure depending on IPO profile. These figures report the median of the Delta coefficient estimated with the modified 3FF model with GARCH-M (in mean) extension using individuals stocks classified into the following groups: (1) high idiosyncratic-risk versus low idiosyncratic-risk IPOs' portfolios (Panel A), (2) young versus mature issuing firms (Panel B), (3) undervalued versus overvalued IPOs' portfolios (Panel C), (4) IPOs depending on their industry (Panel D) and (5) IPOs depending on their issuance period (hot for issues in 2000, quiet for issues between 2001 and 2007 and crisis for issues between 2008 and 2009). The Delta coefficient measures the individual returns sensitivity to firm-level idiosyncratic risk over the 12 first quarters of IPO trading. Delta is our proxy for idiosyncratic risk exposure

On the one hand, we have discussed that hot-market issues are characterized by high levels of idiosyncratic risk. It seems that investors are more vigilant in periods of high volume of issues than in other periods, which leads them to require an additionally risk premium to incorporate the specific risk of the firm into the aftermarket prices. On the other hand, Mriisa Bouden (2015) show that underwriters tend to undervalue (overvalue) the issue in the pre-IPO when they (do not) incorporate information associated with the idiosyncratic risk components into IPO prices. Benveniste and Spindt (1989) consider IPO underpricing as a compensation for informed investors to motivate them to reveal their private information about the issue. Thus, IPO underpricing mitigates the level of information asymmetry between issuers and investors. For this reason, it is easier for investors to incorporate idiosyncratic risk into the prices of undervalued issues than those of overvalued issues. This could explain the higher level of idiosyncratic risk exposure of undervalued IPOs compared with overvalued IPOs.

Moreover, we show that the high exposure of hot-market IPOs to the idiosyncratic risk could explain the long-run underperformance of these IPOs with respect to issues in the quiet period. Results in Panel (B) of Table 6 show higher levels of “Betas”<sup>31</sup> for hot issues (the median of the “Betas” distribution equals 1.8) and high idiosyncratic-risk IPOs (the median of the “Betas” distribution equals 1.7). We previously noted that IPOs in a hot-issue market exhibit high levels of idiosyncratic risk. We add that this type of IPOs is more affected by systematic risk factors. Results in Panel (B) of Table 6 confirm this finding by showing a significant difference in “Betas” between high and low idiosyncratic-risk IPOs (the median sum of Betas is 1.7 against 1.4, respectively). These results show that the difference in abnormal returns between these two types of IPOs can be attributed to the difference in systematic risk factors. These findings are consistent with Ang et al. (2006) who show that high-idiosyncratic risk stocks which are sensitive to market volatility risk exhibit low long-run returns. However, our empirical evidence supports these findings for IPOs only.

Other results show that there is no significant difference in either the impact of the systematic risk factors<sup>32</sup> or the idiosyncratic risk<sup>33</sup> between high and low idiosyncratic-risk matched non-IPOs. Therefore, unlike for IPOs, the difference in intercepts from the modified 3FF model between high ( $-0.014\%$ <sup>34</sup>) and low idiosyncratic-risk ( $-0.007\%$ <sup>35</sup>) matched non-IPOs is not significant. We conclude from our results that the negative cross-section relationship between firm-level idiosyncratic volatility and abnormal performance documented by Ang et al. (2006) is primarily derived from the IPO market and is generally valid for established stocks in the market.<sup>36</sup>

Overall, results in Table 6 show that the idiosyncratic volatility impact on IPO long-run performance depends on the IPO profile. Our findings support the alternative hypothesis of a significant impact of idiosyncratic volatility on IPO individual event-time long-run returns for all types of IPOs, except overvalued IPOs and issues in the crisis period. We conclude that the difference in abnormal performance between IPOs,

<sup>31</sup> Systematic risk impact is measured by the sum of “Beta” coefficients tied to the market, size, and book-to-market factors.

<sup>32</sup> The median sum of “Betas” is 1.1 for high idiosyncratic-risk matched non-IPOs versus 1.3 for low idiosyncratic-risk matched non-IPOs.

<sup>33</sup> The median “Delta” is 0.4 for high idiosyncratic-risk matched non-IPOs against 0.1 for low idiosyncratic-risk matched non-IPOs.

<sup>34</sup> With a Wilcoxon  $p$  value of 0.01.

<sup>35</sup> With a Wilcoxon  $p$  value of 0.16.

<sup>36</sup> The sample period in Ang et al. (2006) study is from January 1986 to December 2000.

regardless of its type, include an abnormality associated with the difference in a firm-level idiosyncratic risk premium.

## 5 Implications for future research, potential investors and decision makers

Our empirical analysis shows that the negative difference in long-run performance between high and low idiosyncratic risk stocks is present only in IPOs. This finding could explain Ang et al.'s (2006) results that show lower returns for high-idiosyncratic risk stocks given the new issue bias. Furthermore, our results for most types of IPOs support the findings of Chen and Petkova (2012) for traded firms, which show that high idiosyncratic volatility is associated with positive idiosyncratic risk exposure. However, unlike established firms, IPOs present a higher level of information asymmetry between issuers and investors. For some cases, this information disparity could cause confusion in the investors' judgment about the risk characteristics of the issued stocks and leads them to not consider an insurance premium associated with their idiosyncratic risk, which results in overvalued IPOs in the short-run and IPO underperformance in the long-run. Hence, our study contributes to the literature by highlighting that future research should distinguish between IPOs and established firms when focusing on: (1) the relationship between firm-level idiosyncratic risk and abnormal performance and (2) the determinants of the idiosyncratic risk exposure.

Moreover, our findings motivate investors to require an additional premium associated with firm-level idiosyncratic risk, especially when they agree to invest in high-risk IPOs, technology firms, and hot new issues. This research also provides investors with an appreciation of IPO profiles that outperform the market in the long run, and hence, achieve profitable IPO investments.

Furthermore, our results show that unlike all IPO categories, overvalued IPOs and firms going public in a crisis period are less exposed to firm-level idiosyncratic risk. If the information asymmetry surrounding the new issue is high, investor opinions will diverge, due to a lack of incorporation of the firm's private information into its stock price. Our findings could lead market regulators to introduce new rules to improve information disclosure during the issuance of new equities especially in crisis periods. For instance, Xiaoqiong et al. (2008) emphasize the role of the regulatory environment and economic reforms that provide a positive signal argument to support Chinese firms after going public. We think that in the future, the focus will be on a better dissemination of information, especially with the new Q4IPO program that offers a platform providing communication between issuing firms and investors. Future research should center on assessing the impact of better information disclosure through the effect of idiosyncratic risk on IPO performance.

## 6 Conclusion

This paper improves upon traditional approaches used in the previous literature to measure abnormal returns and presents a new approach that accounts for firm-specific risk to elucidate the variation in IPO performance in the long run. In sum, the standard 3FF model,

often used to assess abnormal returns, does not consider firm-specific risk. Consequently, abnormal returns measured with the standard 3FF model are only adjusted for risk associated with common factors (market, size, and book-to-market). As the firm-specific risk varies over time, we add a GARCH-M (in mean) extension to the standard 3FF model to account for the conditional idiosyncratic volatility in the individual returns' equation through the IPO event-time method.

First, our results show a positive and significant relationship between 3-year firm-level idiosyncratic volatility and individual expected returns for almost all IPOs, except overvalued issues and firms going public in a crisis period. This long-run relationship between idiosyncratic risk and expected returns is more important in hot-issue markets and for IPOs presenting specific characteristics (undervalued IPOs, high idiosyncratic-risk issues in the first quarter of IPO trading and HITEC issuing firms). In those cases, abnormal returns assessed with the standard 3FF model is not accurate because it only partly includes firm-specific risk effect on expected returns. Consequently, we find that the difference in long-run abnormal returns between IPOs and comparable non-IPOs loses its significance when abnormal returns are adjusted for firm-level idiosyncratic risk using the modified 3FF model with GARCH-M. Our results are consistent with Barber and Lyon (1997), Kothari and Warner (1997), and Gompers and Lerner's (2003) findings which attribute the mixed evidence in the behavior of IPO performance to the methodology used to compute long-run abnormal returns. We add to this literature that the inclusion of an idiosyncratic risk factor influences the apparent performance of IPOs in the long run. Thus, this paper suggests that a part of abnormal returns in specific IPOs long-run performance is derived from firm idiosyncratic risk.

Second, our findings show that the event time variation in idiosyncratic risk depends on the type of equity (IPO or non-IPO). We note that IPOs exhibit higher idiosyncratic risk than their non-IPO peers, especially during the early aftermarket stage. As time goes by, the level of IPO idiosyncratic risk gradually approaches that of similar non-IPO towards the end of the third year of IPO trading. We also find that high levels of IPO idiosyncratic volatility over the first 3 years of the offering are mostly concentrated among high idiosyncratic-risk IPOs in the early aftermarket stage, young IPOs, overvalued IPOs, technology firms and hot-market issues. It is well known that these types of IPOs are subject to a great divergence of opinions among investors, which is reflected by the great variability in their returns and inferred in high levels of idiosyncratic volatility.

Third, we note that the idiosyncratic risk exposure is more pronounced for high-idiosyncratic risk IPOs (such as technology and hot issues). This finding is consistent with Chen and Petkova (2012) who show high idiosyncratic risk exposure for high-idiosyncratic risk stocks. However, we add that unlike established firms, we should consider the asymmetric information problem which characterizes the IPO market in general and especially some types of IPOs such as the overvalued issues. We show that when underwriters overvalue the new issues with respect to their peers in the pre-IPO, investors (especially the uninformed ones who most likely receive a full allocation of overvalued issues), are unable to incorporate idiosyncratic risk into aftermarket prices of these overvalued issues. We infer that even the issue is categorized among high idiosyncratic-risk stocks such as the case of overvalued issues; the information asymmetry level around its pre-IPO valuation affects the degree of idiosyncratic risk integration into its aftermarket prices.

Finally, we conclude that it is interesting to distinguish between IPOs and established firms on the one hand, and consider several characteristics of IPOs on the other hand, when we consider the impact of the idiosyncratic risk on returns to provide a better model of IPO long-run performance. Future research should concentrate on the development of a

better measure of the idiosyncratic risk factor as well as the different determinants of the IPO idiosyncratic risk exposure to better analyze its role on the long-run IPO performance measurement.

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