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Firm life cycle and idiosyncratic volatility☆

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ABSTRACT

This paper investigates the association between idiosyncratic volatility and firm life cycle stages. Since firm performance and availability of information vary across life cycle stages, and such variation affects uncertainty about future cash flows and stock returns, we argue that idiosyncratic volatility also varies across firm life cycle stages. Using US data, this study shows that idiosyncratic volatility is significantly higher in the introduction and decline stages, and significantly lower in the growth and mature stages, when compared to that in the shake-out stage. Our study also reveals that the roles of both cash flow volatility and information uncertainty in affecting idiosyncratic volatility vary depending on firm life cycle stages. Our results are robust to alternative specifications of life cycle proxies and idiosyncratic volatility, and to an alternative regression specification.

1. Introduction

This paper examines the variation in idiosyncratic volatility (IVOL) across firm life cycle stages, and evaluates the roles of fundamental uncertainty and information uncertainty in explaining this variation. IVOL reflects firm specific return volatility, which results primarily from a firm's actions and is independent of the common market movement. The motivation for this study comes from the observation that IVOL accounts for most of the variation in the risk of an individual stock over time (Campbell, Lettau, Malkiel, & Xu, 2001; Morck, Yeung, & Yu, 2000). Accordingly, the potential determinants and the market pricing of IVOL have become one of the most actively researched topics in the asset-pricing arena. Another motivation stems from the mixed evidence in the finance literature (explained below) that attempts to explain the role of firm age in affecting IVOL. IVOL has important implications for portfolio management, diversification strategy, arbitrage process, valuation of employee stock options and managerial compensation policies (March & Shapira, 1987; Weber, 2004).

Several recent papers suggest that product market competition (Gaspar & Massa, 2006), option-based compensation (Chen, Steiner, & Whyte, 2006; Meulbroek, 2001), cash flow volatility and corporate growth options (Irvine & Pontiff, 2009; Wei & Zhang, 2006; Cao, Simin, & Zhao, 2008), business cycle (Bekaert, Hodrick, & Zhang, 2012), and deteriorating financial reporting quality (Rajgopal & Venkatachalam, 2011) have been largely responsible for a surge in IVOL over time. Moreover, Brown and Kapadia (2007) and Fink, Fink, Grullon, and Weston (2010) show that a decline in maturity of the typical US public firm is associated positively with IVOL. Prior studies overwhelmingly use firm age as a life cycle proxy. Some studies show that IVOL is lower for older firms (Fink et al., 2010; Gaspar & Massa, 2006). In contrast, other studies find a positive association between age and IVOL (Luo & Bhattacharya, 2009; Ferreira & Laux, 2007), whereas another study finds no association between them (Tan & Liu, 2016). We argue that this mixed evidence relates to the use of firm age as a proxy for life cycle: a measure that ascribes a *linear* progression from birth to decline and largely fails to capture the dynamism in a firm's transition from one stage to another. We incorporate a 'dynamic resource-based view' as a theoretical lens for understanding IVOL in different life cycle stages. Recent evidence suggests that firms non-monotonically move back and forth in their life cycle (Dickinson, 2011), and experience varying fundamental risk and information uncertainty at different life cycle stages (Al-Hadi, Hasan, & Habib, 2016; Dickinson, 2011, Habib & Hasan, in press). Therefore, it is important to understand the implications of non-linear life cycle stages for IVOL using a precise proxy that can capture the dynamic nature of firm life cycles.

Firm life cycle theory proposes that the resources, capabilities, strategies, structures and functioning of the firm vary significantly with particular stages of development (Miller & Friesen, 1980, 1984; Quinn & Cameron, 1983). Recent empirical studies suggest that firm life cycle is a combination of observable and unobservable, internal and external, firm, manager, and macro-economic characteristics. As such, it is an inherent and time-varying factor that is able to predict financial policy (e.g., dividend policy, cash holdings, and capital structure), firm

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performance, and disclosure level (Al-Hadi et al., 2016; DeAngelo, DeAngelo, & Stulz, 2006; Dickinson, 2011; Faff, Kwok, Podolski, & Wong, 2016). We argue that the strong firm performance and the superior information environment associated with growth and mature firms reduce uncertainty about future cash flows and stock returns, and this reduced uncertainty, in turn, reduces IVOL. On the other hand, introduction and decline stage firms are exposed to weaker firm performance and a poor information environment, both of which increase uncertainty about future cash flows and returns and, therefore, IVOL.

Given that future cash flow and information uncertainties increase IVOL (Irvine & Pontiff, 2009; Rajgopal & Venkatachalam, 2011), and these uncertainties vary across the life cycle stages (Al-Hadi et al., 2016; Dickinson, 2011; Kimberly & Miles, 1980), we examine how such variations differentially affect IVOL. Firms in the introduction (decline) stages are exposed to uncertain and volatile cash flow because of the 'liability of newness' ('liability of senescence'). During the growth and mature stages, firms establish their brand identity and market share and, thereby, enjoy an increasing profitability and a reducing future cash flow volatility. Thus, varying cash flow volatility at different life cycle stages should moderate the association between idiosyncratic volatility and life cycle stages. We also investigate how variation in the information uncertainty across the life cycle stages affects IVOL. Given the higher (lower) firm-specific disclosures during growth and mature (introduction and decline) stages (Al-Hadi et al., 2016), we expect the varying information uncertainty across the life cycle stages to moderate the association between IVOL and life cycle stages.

Using the Dickinson (2011) five-stage life cycle model, we find IVOL to be higher in the introduction and decline stages of the firm life cycle compared to the shake-out stage,[1] but lower in the growth and mature stages of the firm life cycle. Our results remain robust even after controlling for firm age and listing cohort, and for other known determinants of IVOL. We also find that, both cash flow volatility and information uncertainty affect IVOL differentially across life cycle stages.

The Brown and Kapadia (2007) and Fink et al. (2010) papers are closely related to our paper. Brown and Kapadia (2007) use listing cohort of the firm, and show that fundamental change in the character of a typical publicly traded firm is largely responsible for surges in the IVOL. Fink et al. (2010), on the other hand, use firm age, and document that an increase in IVOL during the internet boom can be attributed to a market-wide decline in maturity of the typical public firm.

While both of the aforementioned studies examine *time trend* in IVOL, we argue that firm age is a noisy proxy for firm life cycle, and there is no guarantee that the documented negative association between firm age and IVOL will also be applicable to the life cycle theory. Both Dickinson (2011) and Faff et al. (2016) stress the importance of using a proper proxy for firm life cycle stages. In particular, they argue that firm age is not a good proxy for life-cycle, because the time required for firms' transition across life cycle stages varies across industries, and firms of the same age can learn at different rates depending on their feedback mechanisms. Moreover, age as a life cycle measure cannot track the transition of a firm across different life cycle stages, since this proxy relies on the assumption that a firm *moves monotonically* through its life cycle (Dickinson, 2011). Our direct measure, on the other hand, is free of this contentious assumption, captures the dynamic nature of life cycle stages and shows that IVOL differs significantly across the life cycle stages. Furthermore, our life cycle proxy incorporates changes in the variation in innate factors across life cycle stages. Therefore, we do not consider life cycle stages as a 'catch all' proxy for explaining the IVOL.

[1] Shake-out is a transitory stage in the firm life cycle. As Dickinson (2011) remarks, the literature clearly spells out the role of all stages of the firm life cycle except for the shake-out stage. As a result, the expected signs of this stage are unclear. Thus, in developing hypotheses, we use the shake-out stage as a basis for comparison with other stages of the firm life cycle.

Our study makes a number of contributions. First, we contribute to the extant theoretical and empirical literature on the determinants of IVOL[2] by documenting the role of firm life cycle in explaining IVOL. Prior research on the association between firm age and IVOL provides mixed evidence as mentioned above. In contrast, based on a more intuitive measure of life cycle (Dickinson, 2011), our results suggest a *non-linear* relation between the IVOL and life cycle stages. Second, we contribute to the life cycle literature by showing the unique role of firm life cycle in explaining cross-sectional variation in IVOL. Recent research in finance and accounting documents the role of firm life cycle in financial policy, performance and the functioning of a firm (DeAngelo et al., 2006; DeAngelo, DeAngelo, & Stulz, 2010; Faff et al., 2016; Habib & Hasan, in press; Hasan, Hossain, Cheung, & Habib, 2015; Koh, Dai, & Chang, 2015). Our study sheds further light on the role of firm life cycle on investors' valuation of the firm. The contribution of our paper may be viewed in the context of its additional validation of the Dickinson (2011) measure, which, to the best of our knowledge, has remained unexplored. Finally, our study has direct implications for investors' portfolio and hedging strategies. For example, high levels of IVOL in the introduction and decline stages indicate low correlations between stocks and, therefore, investors holding stock of introduction and decline firms need to increase the number of securities required to generate a well-diversified portfolio (see Campbell et al., 2001, pp. 23–27). Moreover, given that IVOL is important in explaining the cross-sectional difference in expected returns (Ang, Hodrick, Xing, & Zhang, 2006; Goyal & Santa-Clara, 2003; Herskovic, Kelly, Lustig, & Van Nieuwerburgh, 2016), our study suggests that investors should appraise IVOL in conjunction with the firm life cycle stages.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses. Section 3 explains research design. Section 4 explains sample selection, descriptive statistics, and regression results. The final section concludes the paper.

2. Hypotheses development

We hypothesize that idiosyncratic volatility will be higher during the introduction phase of the firm life cycle because of uncertain profitability and cash flows (Habib & Hasan, in press; Irvine & Pontiff, 2009; Pástor & Veronesi, 2003). A high degree of information asymmetry between managers and investors during this stage allows managers to invest in diversifying strategies inefficiently, enter into hedging and insurance relationships, or seek opportunities to increase the longevity of the company, to the detriment of short-run optimization (Donaldson & Lorsch, 1983; Doukas & Kan, 2004). Although firms in the growth stage of the life cycle have insufficient resource base, these firms are promising, profitable, and have strong potential and less uncertainty about cash flow (Dickinson, 2011; Spence, 1977, 1979, 1981). The characteristics of growth firms attract greater analyst coverage, attaining potential benefits from private information acquisition (Barth, Kasznik, & McNichols, 2001; Lehavy, Li, & Merkley, 2011). Greater analyst coverage, in turn, reduces mispricing and information asymmetry (Barth et al., 2001; Brennan & Subrahmanyam, 1995), and should reduce IVOL.

Firms in the mature stage of the life cycle are relatively larger, more profitable, and generate larger operating cash flows. Owing to their large customer base and diversification advantage, these firms are exposed to relatively less cash flow risk. Moreover, mature firms, having had a long existence in the market, are more closely followed by analysts and investors. Thus, these attributes of mature firms help to reduce

[2] The market pricing of IVOL has also been a topic of intense research. Although modern risk-based asset pricing theories (e.g., Sharpe, 1964) maintain that IVOL is not a priced risk factor, research finding in favor of market pricing include Ang et al. (2006), Lui, Markov, and Tamayo (2007), and Goyal and Santa-Clara (2003). On the other hand, evidence supporting the contention that IVOL is not a priced factor include Bali and Cakici (2008), Huang, Liu, Rhee, and Zhang (2010), Khovansky and Zhylyevskyy (2013) and Han and Lesmond (2011).

investors' uncertainty about future returns and, therefore, we conjecture that mature firms are associated with less IVOL.

During the decline stage of the firm life cycle, declining growth leads to declining prices (Wernerfelt, 1985). Additional investments during the declining phase are justified by the drive for a return to profitability (Dickinson, 2011) but, with declining growth, returns from investment become uncertain. Thus, reduced or negative profitability and cash flow, and increasing earnings- and cash flow-volatility in the decline stage increase investors' uncertainty, with a consequent increase in IVOL. Based on the preceding arguments we develop the following hypothesis:

H1. *When compared to the shake-out stage of the firm life cycle, IVOL is higher during the introduction and decline stages but lower during the growth and maturity stages.*

2.1. Cash flow volatility, life cycle stages, and IVOL

Cash flow volatility, a component of fundamental uncertainty, captures uncertainty about the perceived value of an investment's future cash flows, expected growth, and risk (Chen, Dhaliwal, & Trombley, 2008), and it has important implications for IVOL. Irvine and Pontiff (2009) document that the trend in cash-flow volatility mirrors the trend in idiosyncratic stock-return volatility. During the introduction phase of the firm life cycle, a firm's resource bases are more fluid and require more risky investment for expansion. Investments during this phase may generate uncertain future returns and volatile cash flows because of low product differentiation, lack of efficiency in the production process, and shortage of financial resources (Liao, 2006; Lynall, Golden, & Hillman, 2003). Uncertain and volatile future cash flows in the introduction stage of firm life cycle, therefore, increase IVOL following the arguments proposed by Pástor and Veronesi (2003). During the decline phase, firms face a relatively high likelihood of exiting the market due to their internal inefficiencies, and the erosion of technology, products, business concepts and management strategies over time. To overcome these limitations and re-gain their market share, firms in the decline stage are likely to increase their investment (Benmelech, Kandel, & Veronesi, 2010; Dickinson, 2011). Investments in negative NPV will generate uncertain and volatile future cash flows, which increases IVOL.

With respect to cash flow during the growth phase, it is suggested that product differentiation generates higher revenues and profit margins (Selling & Stickney, 1989), and growth firms are likely to exert the greatest effort to establish their brand identity and market share (Dickinson, 2011). Furthermore, substantial investments during the introduction phase start generating returns during the growth phase: a positive implication for future profitability and cash flow stability that decreases IVOL. Finally, cash flow volatility decreases for mature firms due to the diversification effects of investing into more market segments, thereby reducing IVOL. Taken together, the above discussion leads us to develop the following hypothesis:

H2A. *When compared with the shake-out stage of the firm life cycle, cash flow volatility-induced IVOL will be higher during the introduction and decline stages but lower during the growth and mature stages.*

2.2. Informational uncertainty, life cycle stages and IVOL

Information uncertainty makes investors' assessment about a firm's performance, cash flow and expected return difficult (Easley & O'hara, 2004; Healy, Hutton, & Palepu, 1999). Financial analysts are a conduit for increasing the amount of firm-specific information available to investors. Analysts mostly use information provided directly by the firm in estimating earnings forecasts (Knutson, 1992; Lees, 1981). Lang and Lundholm (1996) provide empirical evidence that firms with more informative disclosure policies have less dispersion among individual analyst forecasts. Barry and Jennings (1992) argue that dispersion in analyst forecast reflects uncertainty about firms' future economic performance. Johnson (2004), too, argues that analyst dispersion is a product of uncertainty about the information environment created by the poor transparency of a firm's practice. Therefore, prior studies also use dispersion in analyst forecasts as a measure of information uncertainty (Gaspar & Massa, 2006; Zhang, 2006).

Extant studies show that growth and mature firms have more incentives and resources for disclosing firm-specific information (Al-Hadi et al., 2016). Following this line of argument, we posit that greater levels of disclosures in the growth and mature stages enable analysts to synthesize information more efficiently, causing a decline in forecast dispersion and IVOL. In a similar vein, information asymmetry in the introduction and decline stages causes an increase forecast dispersion, which also increases idiosyncratic volatility.

H2B. *When compared with the shake-out stage of the firm life cycle, information uncertainty induced IVOL will be higher during the introduction and decline stages but lower during the growth and mature stages.*

3. Research design

3.1. Sample and data

We collect data for this study from four sources: financial information from the Compustat annual database, stock returns and prices data from the Centre for Research in Security Prices (CRSP), analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S) and, finally, daily factor data (e.g., SMB, HML, and UMD) from the Kenneth R. French web site.[3] We begin with a total of 301,112 firm-year observations retrieved from Compustat annual data from 1987 to 2013.[4] We then exclude financial (SIC 6000–6999) (76,004 firm years) and utility (SIC 4900–4949) (11,523 firm years) firms, and stock traded outside NYSE, AMEX and NASDAQ (EXCHG = 11, 12 and 14) (99,979 firm years).[5] We also exclude observations with missing values in the measurement of key dependent, independent and control variables (a total of 49,090 firm years). Our final sample consists of 64,516 firm year observations with 6944 unique firms. The number of observations in any given regression varies depending on the model-specific data requirements. To avoid the undesirable influence of outliers, we winsorize the key variables in the extreme 1% of the respective distributions. Table 1 presents the sample selection (Panel A) and industry distribution of the sample (Panel B). Variable definitions are presented in the Appendix A.

Table 1, Panel B reports the composition of the sample by the 12 industry groups. The sample is not evenly distributed across industries (with the largest sample being in the business equipment (24.26%) and other (14.16%) industries, respectively).

3.2. Empirical model

We test the association between IVOL and firm life cycle using the following regression model:

$$\begin{aligned} IVOL_{i,t} = \gamma_0 + \sum_{j=1}^{4} \gamma_j LCS_{i,t} + \gamma_5 SIZE_{i,t} + \gamma_6 LEV_{i,t} + \gamma_7 MTB_{i,t} + \gamma_8 ROE_{i,t} + \gamma_9 DIV_{i,t} + \gamma_{10} SD\_CF_{i,t} \\ + \gamma_{11} HINDEX_{i,t} + \gamma_{12} AGE_{i,t} + \gamma_{13} RET_{i,t} + \gamma_{14} FRQ_{i,t} + \textstyle\sum_t \gamma_t \mathrm{YEAR_t} + \sum_t \gamma_t \mathrm{IND_t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research. We thank Kenneth French for making these data available.

[4] However, our first year of regression began from 1991 as we used a three year rolling standard deviation of cash flow from operation (*OANCF*) scaled by total assets (*AT*) (denoted as *SD_CF*).

[5] Our inference remains the same, even if we do not exclude the firms listed outside NYSE, AMEX and NASDAQ.

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Table 1
Sample selection and distribution of the sample.

Panel A: Data and sample

Description	Total number of observations
Data available in the Compustat fundamentals annual file from 1987 to 2013	301,112
Less:	
Financial and utility firms (76,004 + 11,523)	(87,527)
Firms listed outside NYSE, AMEX and NASDAQ	(99,979)
Firms with missing cash flow (life cycle proxy)	(11,086)
Firms with missing IVOL variable	(17,466)
Firms with missing values for the variables used in the regression model	(20,538)
Final sample	**64,516**
Final number of unique firms	**6944**

Panel B: Industry distribution

Industry name	Total number of observations	% of observations
Consumer nondurables	4219	6.54%
Consumer durables	1670	2.59%
Manufacturing	8745	13.55%
Oil, gas and coal extraction and products	3996	6.19%
Chemicals and allied products	2147	3.33%
Business equipment	15,651	24.26%
Telephone and television transmission	2456	3.81%
Wholesale, retail and some services	7372	11.43%
Healthcare, medical equipment and drugs	9124	14.14%
Other	9136	14.16%
Total	**64,516**	100.00%

where IVOL indicates idiosyncratic volatility and LCS is firm life cycle stages following Dickinson (2011). Other variables are defined in the Appendix A.

To test the moderating effects of fundamental risk and information uncertainty, we expand Eq. (1) as below:

$$\begin{aligned} IVOL_{i,t} = {} & \gamma_0 + \sum_{j=1}^{4} \gamma_j LCS_{i,t} + \gamma_5 SD\_CF_{i,t} + \sum_{K=6}^{9} \gamma_k LCS_{i,t} * SD\_CF_{i,t} + \gamma_{10} SIZE_{i,t} + \gamma_{11} LEV_{i,t} \\ & + \gamma_{12} MTB_{i,t} + \gamma_{13} ROE_{i,t} + \gamma_{14} DIV_{i,t} + \gamma_{15} HINDEX_{i,t} + \gamma_{16} AGE_{i,t} + \gamma_{17} RET_{i,t} \\ & + \gamma_{18} FRQ_{i,t} + \sum\nolimits_t \gamma_t \mathrm{YEAR}_t + \sum\nolimits_t \gamma_t \mathrm{IND}_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

In Eq. (2), *SD_CF* denotes volatility of cash flow, a proxy for fundamental uncertainty (Irvine & Pontiff, 2009), which is measured as the rolling standard deviation of cash flow from operation (*OANCF*) scaled by total assets (*AT*) over the previous three years.

$$\begin{aligned} IVOL_{i,t} = {} & \gamma_0 + \sum_{j=1}^{4} \gamma_j LCS_{i,t} + \gamma_5 DISP_{i,t} + \sum_{K=6}^{9} \gamma_k LCS_{i,t} * DISP_{i,t} + \gamma_{10} SIZE_{i,t} + \gamma_{11} LEV_{i,t} \\ & + \gamma_{12} MTB_{i,t} + \gamma_{13} ROE_{i,t} + \gamma_{14} DIV_{i,t} + \gamma_{15} SD\_CF_{i,t} + \gamma_{16} HINDEX_{i,t} \\ & + \gamma_{17} AGE_{i,t} + \gamma_{18} RET_{i,t} + \gamma_{19} FRQ_{i,t} + \sum\nolimits_t \gamma_t \mathrm{YEAR}_t + \sum\nolimits_t \gamma_t \mathrm{IND}_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In Eq. (3), *DISP* is analyst forecast dispersion, a proxy for information uncertainty (Zhang, 2006). *DISP* is estimated immediately before the end of the fiscal year and is scaled by the price at the end of the previous year, and we require at least three analyst forecasts to compute forecast dispersion. We retrieve analyst forecast data from the I/B/E/S adjusted Detail data files because "The data provided on the Detail files are rounded to four decimals, indicating that the rounding [problems] are less severe if the Detail files are used" (Payne & Thomas, 2003, p.1050). We also retrieve actual earnings per share from the I/B/E/S to make them comparable to forecasted EPS.

3.3. Dependent variables: idiosyncratic return volatility

We use daily stock returns as a basis for calculating annual estimates of IRV. In doing so, we run the following CAPM and Fama and French (1993) three-factor regressions for each firm in each year. We require at least 175 daily observations to compute IRV.

3.3.1. CAPM model

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \varepsilon_{i,t}, \quad i = 1, \ldots, N \text{ and } t = 1, \ldots, T \tag{4}$$

where $R_{i,t}$ is the stock return on day t for firm i, $R_{f,t}$ is the simple daily return from holding a 30-day risk-free treasury-bill, $R_{m,t}$ is the daily return from the CRSP value-weighted market index, α_i (or alpha) is the intercept term, β_i (or beta) is the slope coefficient that captures systematic risk, and $\varepsilon_{i,t}$ is an error term. The standard deviation of the residuals from the above regression model is our annual measure of IRV.

3.3.2. Fama and French (1993) model

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \gamma_i SMB_t + \varphi_i HML_t + \varepsilon_{i,t}, \tag{5}$$

where SMB_t and HML_t are the size premium (Small minus Big) and the value premium (High minus Low) respectively, collected from Kenneth French's website, and remaining variables are as in Eq. (4).[6]

3.4. Independent variable: estimation of firm life cycle stages

We follow Dickinson (2011) in order to develop proxies for the firms' stage in the life cycle.[7] Dickinson (2011) argues that cash flows capture differences in a firm's profitability, growth and risk and, hence, that one may use the cash flow from operating (*OANCF*), investing (*IVNCF*) and financing (*FINCF*) to group firms into life cycle stages such as: 'introduction', 'growth', 'mature', 'shake-out' and 'decline'.[8] The methodology is based on the following cash flow pattern classification:

(1) Introduction: if $OANCF < 0$, $IVNCF < 0$ and $FINCF > 0$;
(2) Growth: if $OANCF > 0$, $IVNCF < 0$ and $FINCF > 0$;
(3) Mature: if $OANCF > 0$, $IVNCF < 0$ and $FINCF < 0$;
(4) Decline: if $OANCF < 0$, $IVNCF > 0$ and $FINCF \leq$ or ≥ 0; and
(5) Shake-out: the remaining firm years will be classified under the shake-out stage.
In addition, in the sensitivity analysis we use DeAngelo et al.'s (2006) life cycle proxies, i.e., retained earnings-to-total assets (*RE/TA*) and retained earnings-to-total equity (*RE/TE*). These proxies measure the extent to which a firm is self-financing or reliant on external capital. A high *RE/TA* and *RE/TE* implies that the

[6] As we, in accord with Brown and Kapadia (2007), intend to examine the idiosyncratic risk of individual firms and relate it to firm-specific characteristics, we use this methodology as opposed to the one proposed by Campbell et al. (2001), which produces average values of idiosyncratic risk for a set of firms (all listed firms in their paper) and, thus, cannot serve our purpose.

[7] Anthony and Ramesh (1992) provide one of the first empirical procedures for classifying firms into different life cycle stages. However, we do not use their method for three reasons. These include: (i) a life cycle classification based on Anthony and Ramesh (1992) requires a five year history of variables, removing true "introduction stage" firms from the sample. Thus, no data (and as such, no meaningful analysis) on introduction stage firms are available; (ii) Dickinson (2011) has shown that the life cycle classification based on the Anthony and Ramesh (1992) procedure leads to an erroneous classification of the stage of firms in the life cycle; (iii) this classification procedure is 'ad hoc' and relies on portfolio sorts to classify the firm into different life cycle stages.

[8] See Dickinson (2011) for detailed discussion of the theoretical motivation for this measure.

firm is more mature or old with declining investment, while the firm with a low *RE*/*TA* and *RE*/*TE* tends to be young and growing (DeAngelo et al., 2006).

3.5. Control variables

Our regression models incorporate a number of control variables that prior studies suggest might affect IVOL. Large firms tend to diversify their businesses more efficiently and are less prone to bankruptcy (Titman & Wessels, 1988). Therefore, these firms experience lower return volatility (Pástor & Veronesi, 2003) and, hence, we control for firm size (*SIZE*) in the regression model. Rajgopal and Venkatachalam (2011) suggest that leverage (*LEV*) increases stockholder risk associated with firm cash flow, suggesting a positive relation between stock return volatility and financial leverage. Cao et al. (2008) and Rajgopal and Venkatachalam (2011) show that firms with more growth opportunities are likely to experience higher IVOL. We control for firm growth by using the market to book (*MTB*) ratio. Prior studies (e.g., Pástor & Veronesi, 2003; Wei & Zhang, 2006) show that a decrease in corporate earnings and an increase in earnings volatility account for the growth in IVOL. Brown and Kapadia (2007) control for dividend payout ratio in examining IVOL in the US stock market. These studies largely argue that higher profitability and stock returns, and lower volatility in profit can enhance companies' ability to lower financial instability and, thus, lessen IVOL. Therefore, in the regression models, we control for firm profitability (*ROE*), stock return (*RET*), dividend payout (*DIV*) and cash flow risk (*SD_CF*).

Gaspar and Massa (2006) and Irvine and Pontiff (2009) suggest that competition among firms has important implications for IVOL. Therefore, we control for market competition using the Herfindahl Index (*HINDEX*). Prior studies (Gaspar & Massa, 2006; Pástor & Veronesi, 2003) suggest that the future cash flows of younger firms are more uncertain than those of older firms, indicating that firm age (*AGE*) affects firm-specific volatility. Finally, Rajgopal and Venkatachalam (2011) suggest that poor earnings quality (FRQ) increases IVOL.

4. Empirical findings and discussion

4.1. Descriptive statistics

Table 2, Panel A, presents descriptive statistics for the key variables used in the study. Results indicate that the annual estimates of mean (median) *IVOL* based on the CAPM models is 3.4% (2.9%), while that based on the Fama-French three-factor model is 3.3% (2.8%). The life cycle-wise sample distribution shows that around 72.7% of the firms fall into the growth and mature stages, which is close to the findings

Table 2

Panel A: Descriptive statistics

Variables	N	Mean	Standard deviation	25%	Median	75%
Idiosyncratic volatility variables						
IVOL_CAPM	64,516	0.034	0.019	0.020	0.029	0.042
IVOL_FF3	64,516	0.033	0.019	0.019	0.028	0.042
Life cycle proxies						
INTRO	64,516	0.116	0.320	0.000	0.000	0.000
GROWTH	64,516	0.307	0.461	0.000	0.000	1.000
MATURE	64,516	0.420	0.494	0.000	0.000	1.000
SHAKE-OUT	64,516	0.091	0.288	0.000	0.000	0.000
DECLINE	64,516	0.066	0.248	0.000	0.000	0.000
Control variables						
SIZE	64,516	5.891	2.093	4.364	5.812	7.266
LEV	64,516	0.165	0.189	0.001	0.109	0.268
MTB	64,516	2.953	4.112	1.219	2.040	3.495
ROE	64,516	0.038	0.699	−0.029	0.122	0.238
DIV	64,516	0.097	0.294	0.000	0.000	0.096
SD_CF	64,516	0.071	0.093	0.022	0.043	0.081
HINDEX	64,516	0.425	0.146	0.318	0.386	0.477
AGE	64,516	2.528	0.840	1.903	2.540	3.154
RET	64,516	0.205	0.702	−0.212	0.086	0.424
FRQ	64,516	0.114	0.140	0.029	0.067	0.141

Note: Variable definitions are provided in the Appendix A. *Descriptive* statistic for *FRQ* is based on untransformed value (i.e., not multiplied by −1).

Panel B: Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
IVOL_FF3 [1]	1.000															
INTRO [2]	0.260	1.000														
GROWTH [3]	−0.065	−0.241	1.000													
MATURE [4]	−0.247	−0.308	−0.566	1.000												
SHAKE-OUT [5]	0.042	−0.115	−0.211	−0.271	1.000											
DECLINE [6]	0.229	−0.096	−0.177	−0.226	−0.084	1.000										
SIZE [7]	−0.601	−0.189	0.079	0.172	−0.066	−0.170	1.000									
LEV [8]	−0.098	−0.042	0.100	0.001	−0.045	−0.081	0.122	1.000								
MTB [9]	−0.018	0.076	0.009	−0.043	−0.042	0.019	0.203	−0.080	1.000							
ROE [10]	−0.259	−0.180	0.067	0.161	−0.012	−0.199	0.200	0.050	−0.162	1.000						
DIV [11]	−0.227	−0.107	−0.057	0.149	0.020	−0.076	0.180	0.070	0.004	0.087	1.000					
SD_CF [12]	0.357	0.287	−0.083	−0.208	−0.010	0.209	−0.253	−0.160	0.131	−0.188	−0.115	1.000				
HINDEX [13]	−0.073	−0.025	−0.015	0.057	−0.007	−0.045	0.005	0.019	−0.039	0.046	0.044	−0.069	1.000			
AGE [14]	−0.342	−0.165	−0.086	0.222	0.031	−0.104	0.247	0.048	−0.067	0.121	0.144	−0.251	0.125	1.000		
RET [15]	0.017	−0.019	0.050	0.005	−0.015	−0.062	0.095	−0.018	0.217	0.085	−0.018	0.013	0.005	−0.012	1.000	
FRQ [16]	−0.024	−0.061	0.013	0.070	−0.018	−0.061	0.012	0.060	−0.048	0.057	0.025	−0.216	0.133	0.089	0.018	1.000

Note: Bold and *italics* variables are significant at $p < 0.001$ and bold only variables are significant at $p < 0.05$.

Table 3

Baseline regression for the association between IVOL and firm life cycle stages $IVOL_{i,t} = \gamma_0 + \sum_{j=1}^{4}\gamma_j LCS_{i,t} + \gamma_5 SIZE_{i,t} + \gamma_6 LEV_{i,t} + \gamma_7 MTB_{i,t} + \gamma_8 ROE_{i,t} + \gamma_9 DIV_{i,t} + \gamma_{10} SDCF_{i,t} + \gamma_{11} HINDEX_{i,t} + \gamma_{12} AGE_{i,t} + \gamma_{13} RET_{i,t} + \gamma_{14} FRQ_{i,t} + \sum_t \gamma_t YEAR_t + \sum_t \gamma_t IND_t + \varepsilon_{i,t}$.......(1)

Variables	(1) IVOL_CAPM OLS	(2) IVOL_FF3 OLS	(3) IVOL_CAPM FFE	(4) IVOL_FF3 FFE	(5) IVOL_CAPM OLS	(6) IVOL_FF3 OLS	(7) IVOL_CAPM FFE	(8) IVOL_FF3 FFE
INTRO	0.011***	0.011***	0.002***	0.002***	0.004***	0.003***	0.002***	0.002***
	[24.13]	[23.73]	[5.30]	[4.96]	[10.79]	[10.45]	[5.34]	[5.07]
GROWTH	−0.004***	−0.005***	−0.003***	−0.003***	−0.002***	−0.002***	−0.001***	−0.001***
	[−13.34]	[−13.57]	[−12.08]	[−12.38]	[−7.63]	[−7.80]	[−4.56]	[−4.69]
MATURE	−0.007***	−0.007***	−0.003***	−0.003***	−0.002***	−0.002***	−0.001***	−0.001***
	[−22.16]	[−22.03]	[−11.56]	[−11.64]	[−9.55]	[−9.33]	[−5.70]	[−5.70]
DECLINE	0.013***	0.013***	0.005***	0.005***	0.005***	0.005***	0.003***	0.003***
	[26.63]	[26.25]	[11.35]	[11.28]	[13.76]	[13.45]	[7.71]	[7.62]
SIZE	–	–	–	–	−0.004***	−0.005***	−0.006***	−0.006***
					[−59.97]	[−59.95]	[−42.47]	[−43.19]
LEV	–	–	–	–	0.002***	0.002***	0.003***	0.003***
					[4.17]	[4.19]	[4.32]	[4.22]
MTB	–	–	–	–	0.000*	0.000	0.000	0.000
					[1.91]	[1.64]	[1.61]	[1.32]
ROE	–	–	–	–	−0.002***	−0.002***	−0.001***	−0.001***
					[−15.30]	[−15.10]	[−9.76]	[−9.64]
DIV	–	–	–	–	−0.004***	−0.004***	−0.002***	−0.002***
					[−18.25]	[−17.75]	[−9.49]	[−9.33]
SD_CF	–	–	–	–	0.019***	0.020***	0.009***	0.009***
					[18.21]	[18.01]	[7.81]	[7.75]
HINDEX	–	–	–	–	−0.000	−0.000	0.008***	0.008***
					[−0.32]	[−0.27]	[4.61]	[4.47]
AGE	–	–	–	–	−0.002***	−0.002***	−0.005***	−0.005***
					[−18.29]	[−17.96]	[−14.23]	[−14.03]
RET	–	–	–	–	0.002***	0.002***	0.003***	0.003***
					[23.51]	[23.30]	[25.82]	[25.94]
FRQ	–	–	–	–	−0.009***	−0.009***	−0.005***	−0.005***
					[−16.38]	[−16.07]	[−10.73]	[−10.57]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Constant	0.030***	0.030***	0.039***	0.039***	0.057***	0.057***	0.069***	0.069***
	[15.05]	[14.88]	[52.09]	[50.76]	[27.33]	[26.96]	[48.07]	[48.01]
Observations	64,516	64,516	64,516	64,516	64,516	64,516	64,516	64,516
Adj. R^2	0.30	0.29	0.64	0.64	0.57	0.56	0.70	0.70
No of firms	6944	6944	6944	6944	6944	6944	6944	6944

Notes: Variable definitions are provided in the Appendix A. Robust t-statistics in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

reported in Dickinson (2011) (75%). Moreover, descriptive statistics show that the average firm has a *SIZE* of 5.89, *LEV* of 16.5%, an *MTB* ratio of 2.95, *ROE* of 3.80%, *SD_CF* of 7.10%, *AGE* of 2.53 years, *RET* of 20.50% and *DIV* of 9.7%.

4.2. Correlation

Table 2, Panel B reports the pair-wise correlation between the variables included in the regression models. As expected, *IVOL* (proxied by *IVOL_FF3* is significantly ($p < 0.001$) positively correlated with the introduction, shake-out and decline stages, while significantly ($p < 0.001$) negatively correlated with the growth and mature stages of the firm life cycle. Importantly, *SD_CF* is significantly positively correlated with the *IVOL* proxy ($\rho = 0.35$; $p < 0.001$), implying that idiosyncratic volatility is higher for firms with more volatile cash flows. In terms of life cycle stages, *SD_CF* is significantly ($p < 0.001$) positively correlated with the introduction and decline stages while being significantly ($p < 0.001$) negatively correlated with the growth and mature stages. Moreover, *SIZE, ROE, LEV* and *RET* are negatively (positively) correlated ($p < 0.001$) with the introduction, shake-out and decline (growth and mature) stages, while *AGE* is positively (negatively) correlated ($p < 0.001$) with the mature and shake-out (introduction, growth and decline) stages. Overall, the correlations among *IVOL*, the life cycle proxies and the control variables are all in the expected direction and, thus, provide support for the validity of our key measures and constructs.

4.3. Regression results

4.3.1. Association of idiosyncratic volatility with firm life cycle stages

Table 3 presents the regression results for Eq. (1) where IVOL proxies (*IVOL_CAPM* and *IVOL_FF3*) are regressed on firm life cycle stages and a set of control variables with clustered standard errors at the firm level (Petersen, 2009). We hypothesized that IVOL is higher (lower) during introduction and decline (growth and mature) stages (H1). We find support for our hypothesis using both the *IVOL_CAPM* and *IVOL_FF3* versions of idiosyncratic volatility.

In Columns (1) and (2) we present OLS regression results where IVOL proxies (*IVOL_CAPM* and *IVOL_FF3*) are regressed on firm life cycle stages, and on year and industry fixed effects. In Column (1), the coefficients on the *INTRO* ($\beta_1 = 0.011$), *GROWTH* ($\beta_2 = -0.004$), *MATURE* ($\beta_3 = -0.007$), and *DECLINE* ($\beta_4 = 0.013$) stages are all significant at $p < 0.01$. We obtain qualitatively similar results when we use *IVOL_FF3* as a proxy for IVOL in Column (2). One may argue that firm fixed effects estimates are critical to control for unobserved time-invariant firm heterogeneity. Therefore, in Columns (3) and (4), we present firm fixed effect (FFE) regression results for both IVOL proxies. Our firm fixed effect regression results are also qualitatively very similar to the OLS results, confirming that our results are not driven by the firm-level unobserved heterogeneity. Thus, these results suggest that firm life cycle has a profound impact on IVOL.

In Columns (5) and (6) we include firm-level controls, in addition to industry and year effects. We continue to find positive and significant

Table 4
Life cycle stages and IVOL: Relation with prior studies. Inclusion of age since foundation (*AGE_FND*) and listing cohorts.

Variables	(1) IVOL_CAPM	(2) IVOL_FF3	(3) IVOL_CAPM	(4) IVOL_FF3	(5) IVOL_CAPM	(6) IVOL_FF3
INTRO	0.003***	0.003***	0.010***	0.010***	0.003***	0.003***
	[8.12]	[7.85]	[21.36]	[21.09]	[8.46]	[8.27]
GROWTH	−0.002***	−0.002***	−0.005***	−0.005***	−0.002***	−0.002***
	[−5.43]	[−5.50]	[−14.38]	[−14.53]	[−8.46]	[−8.56]
MATURE	−0.002***	−0.002***	−0.007***	−0.007***	−0.002***	−0.002***
	[−6.72]	[−6.51]	[−21.15]	[−20.98]	[−9.32]	[−9.08]
DECLINE	0.004***	0.004***	0.012***	0.012***	0.005***	0.005***
	[9.73]	[9.43]	[23.44]	[23.18]	[11.76]	[11.57]
AGE_FND	−0.002***	−0.002***	–	–	–	–
	[−12.32]	[−12.04]				
Pre-1965 listing dummy	–	–	NA	NA	NA	NA
1965–1974 listing dummy	–	–	0.006***	0.006***	−0.004***	−0.004***
			[9.22]	[9.20]	[−6.08]	[−6.17]
1975–1984 listing dummy	–	–	0.012***	0.013***	−0.002***	−0.002***
			[17.81]	[17.75]	[−2.85]	[−2.97]
1985–1994 listing dummy	–	–	0.013***	0.013***	−0.003***	−0.003***
			[23.68]	[23.50]	[−5.01]	[−5.22]
1995–2004 listing dummy	–	–	0.012***	0.012***	-0.003***	-0.003***
			[21.98]	[21.69]	[−4.84]	[−5.12]
2005–2013 listing dummy	–	–	0.011***	0.011***	−0.007***	−0.007***
			[17.71]	[17.66]	[−9.50]	[−9.52]
Other control variables	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.066***	0.066***	0.022***	0.021***	0.069***	0.070***
	[20.97]	[20.69]	[12.94]	[12.77]	[33.84]	[33.53]
Observations	34,138	34,138	64,516	64,516	64,516	64,516
Adj. R^2	0.57	0.56	0.22	0.21	0.49	0.50
No of firms	4104	4104	6944	6944	6944	6944

Notes: Variable definitions are provided in the Appendix A. Robust t-statistics in brackets *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

($p < 0.01$) coefficients on the *INTRO* ($\beta_1 = 0.004$) and *DECLINE* ($\beta_4 = 0.005$) stages, while negative and significant ($p < 0.01$) coefficients are found on the *GROWTH* ($\beta_2 = -0.002$) and *MATURE* ($\beta_3 = 0.002$) stages.[9] Finally, in Columns (7) and (8), we re-run the regression using a firm fixed effect model, which also includes firm-level controls in addition to the year effect. The firm fixed effect regression specification also confirms a positive (negative) association between IVOL and the introduction and decline (growth and mature) stages.

The regression results in Table 3 show that the coefficients for most of the control variables have the predicted signs and statistical significance. For example, in accord with the empirical findings we find that large (*SIZE*), profitable (*ROE*) firms and firms with better financial reporting quality (*FRQ*) have a lower level of IVOL, but leveraged firms (*LEV*) and firms with volatile cash flows (*SD_CF*) experience more IVOL.[10] We also find that older firms (*AGE*) tend to be negatively associated with IVOL. At first, this seems puzzling, because should our life cycle stages capture a true stage of the firm life cycle, *AGE* would have become insignificant. The answer to the puzzle could be that firm age captures the reputation of the firm (Diamond & Verrecchia, 1991; Gompers, 1996), learning about a firm and uncertainty about future profitability (Pástor & Veronesi, 2003), as well as life expectancy and survival possibility (Cefis & Marsili, 2006). As age increases, investors become more informed about the firms, whereas uncertainty about future profitability decreases, leading to lower idiosyncratic volatility. The weak correlation between firm age and life cycle stages (Table 2, Panel B) also provides evidence that firm age captures attributes other than the life cycle stages.

Finally, the positive (negative) coefficient of *RET* (*MTB*) is consistent with the findings of Brown and Kapadia (2007), and Chen, Huang, and Jha (2012a), Chen, Lu, and Sougiannis (2012b)), respectively.

4.3.2. IVOL and firm life cycle stages: relation with prior studies

4.3.2.1. Relation with Fink et al. (2010). Fink et al. (2010) use firm age (*AGE*) to proxy for firm maturity, and measure *AGE* beginning from the year of founding/incorporation so that the *AGE* variable is not spuriously affected by the fluctuations in the timing of when firms go public. They document that the market-wide decline in maturity of the typical public firm can explain most of the spike in volatility during the late 1990s. In our main analysis (Table 3) we control for firm age, which is measured as the number of years since the firm was first covered by the CRSP (DATADATE – BEGDAT). One may argue that our life cycle variables may be correlated with this *AGE* variable and, therefore, our result would likely weaken, and perhaps disappear, if the Fink et al. (2010) *AGE* variable is controlled for. To alleviate this concern, we re-estimate our regression after including the *AGE_FND*, age variable as used in Fink et al. (2010). To construct this variable, we use data collected by Loughran and Ritter (2004) on the founding dates for a large sample of firms between 1975 and 2015.[11] Regression results tabulated in Table 4 [Columns (1) and (2)] show that the association between firm life cycle stages and IVOL remains robust even after including *AGE_FND*.[12] This result suggests that age cannot truly capture the dynamics in firm life cycle stages, reinforcing our use of a precise proxy to examine the association between IVOL and the dynamic nature of firm life cycle stages.

4.3.2.2. Relation with Brown and Kapadia (2007). Brown and Kapadia (2007) show that the listing groups of firms explain the time trend of

[9] In order to mitigate the concern that our results might be biased because of the multicollinearity problem, we checked the variance inflation factor (VIF) values. We find that multicollinearity is not a problem as the highest VIF is 3.37, related to the *MATURE* stage, followed by 3.13 for the *GROWTH* stage. The rest of the VIFs pertinent to variables are below 2.11.

[10] *FRQ* is estimated by the performance-matched discretionary accruals (*DAC*) model developed by Kothari et al. (2005). Our results remain qualitatively similar even when the Jones and the modified-Jones models (i.e., the modification by Dechow, Sloan, and Sweeney (1995) are used.

[11] https://site.warrington.ufl.edu/ritter/files/2015/08/age7515.xlsx. We thank the authors for making these data available.

[12] Our sample decreases from to 64,516 to 34,138 firm years when *AGE_FND* is used in the regression.

Table 5

Cash flow volatility, life cycle stages and IVOL

$$IVOL_{i,t} = \gamma_0 + \sum_{j=1}^{4} \gamma_j LCS_{i,t} + \gamma_5 SDCF_{i,t} + \sum_{K=6}^{9} \gamma_k LCS_{i,t} * SDCF_{i,t} + \gamma_{10} SIZE_{i,t} + \gamma_{11} LEV_{i,t} + \gamma_{12} MTB_{i,t} + \gamma_{13} ROE_{i,t} + \gamma_{14} DIV_{i,t} + \gamma_{15} HINDEX_{i,t} + \gamma_{16} AGE_{i,t} + \gamma_{17} RET_{i,t} + \gamma_{18} FRQ_{i,t} + \sum_t \gamma_t \mathrm{YEAR}_t + \sum_t \gamma_t \mathrm{IND}_t + \varepsilon_{i,t} \ldots\ldots(2).$$

Variables	(1) IVOL_CAPM	(2) IVOL_FF3
INTRO	0.004***	0.004***
	[9.12]	[8.83]
GROWTH	−0.001***	−0.001***
	[−4.25]	[−4.37]
MATURE	−0.001***	−0.001***
	[−3.81]	[−3.60]
DECLINE	0.006***	0.006***
	[11.19]	[10.93]
SD_CF	0.003***	0.003***
	[7.79]	[7.77]
INTRO * SD_CF	−0.000	−0.000
	[−0.12]	[−0.01]
GROWTH * SD_CF	−0.002***	−0.002***
	[−4.78]	[−4.83]
MATURE*SD_CF	−0.003***	−0.003***
	[−6.08]	[−6.18]
DECLINE*SD_CF	0.001	0.001
	[0.96]	[1.11]
SIZE	−0.004***	−0.004***
	[−57.70]	[−57.80]
LEV	0.009***	0.009***
	[15.26]	[15.39]
MTB	0.000***	0.000***
	[9.17]	[8.96]
ROE	−0.000	−0.000
	[−0.41]	[−0.45]
DIV	−0.003***	−0.003***
	[−13.62]	[−13.00]
HINDEX	−0.001	−0.001
	[−0.75]	[−0.70]
AGE	−0.002***	−0.002***
	[−17.99]	[−17.83]
RET	0.002***	0.002***
	[22.92]	[22.82]
FRQ	−0.011***	−0.011***
	[−20.49]	[−20.18]
Year FE	Yes	Yes
Industry FE	Yes	Yes
Constant	0.055***	0.055***
	[26.24]	[25.95]
Observations	64,516	64,516
Adj. R^2	0.56	0.56
No of firms	6944	6944

Notes: Variable definitions are provided in the Appendix A. Robust t-statistics in brackets *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

IVOL. In particular, they include dummy variables for each ten-year listing group in the regression model and document that the coefficients of the dummy variables increase monotonically over time. One may argue that our main regression results suffer from omitted variable problems, as we do not include listing cohorts in our regression estimates. To allay this concern, we re-estimate our main regression results after including listing cohorts. In Table 4 [Columns (3) and (4)], we include firm life cycle stages and listing cohort dummies, and controls for industry effects. Regression results show that coefficients for *INTRO* and *DECLINE* are positive and significant ($p < 0.01$), while that for *GROWTH* and *MATURE* are negative and significant ($p < 0.01$). Furthermore, coefficients on listing dummies are to a large extent consistent with those of Brown and Kapadia (2007). In Columns (5) and (6) we include firm-level controls in addition to listing cohorts and industry effects. Regression results continue to show positive (negative) and significant ($p < 0.01$) coefficients for the *INTRO* and *DECLINE* (*GROWTH* and *MATURE*) stages. Interestingly, after including firm life cycle stages, firm level controls, industry and year effects, the coefficients on the listing cohort variable change signs but not statistical significance. Therefore, we feel reassured of our empirical findings.

4.3.3. Cash flow volatility, firm life cycle, and IVOL

Table 5 presents regression results for the hypothesis that the role of cash flow volatility in affecting IVOL varies depending on the firm life cycle stages. Following prior literature (e.g., Aiken, West, & Reno, 1991; Chen, Huang, et al., 2012; Chen, Lu, et al., 2012b; Dhaliwal, Judd, Serfling, & Shaikh, 2016), continuous variables used in the interaction terms are first mean-centered, to mitigate multicollinearity problems and facilitate the interpretation of the main effects. As expected, regression results show that *SD_CF*, our proxy for cash flow risk, is positively associated with *IVOL*: the coefficient of *SD_CF* is 0.003 ($p < 0.01$).[13] Our main variables of interest are the interactive coefficients. Regression results show that interactions of *INTRO* and *DECLINE* with *SD_CF* (i.e., *INTRO*SD_CF* and *DECLINE*SD_CF*) are insignificant, implying that the cash flow volatility of these stages is no different from the baseline case (*SHAKE-OUT*) in affecting IVOL. The interactions of the *GROWTH* and

[13] We admit the inherent limitation of *SD_CF* as a proxy for future cash flow uncertainty. A more suitable proxy capturing investors' uncertainty about future cash flow could help us get a better sense of what life cycle stage is picking up. The empirical analysis, therefore, should be evaluated in light of this shortcoming.

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MATURE stages with *SD_CF* (i.e., *GROWTH**SD_CF* and *MATURE**SD_CF*) are negative and significant (e.g., the coefficient for *GROWTH**SD_CF* is −0.002 and that for *MATURE**SD_CF* is −0.003; both significant at $p < 0.01$). The interactive coefficients thus indicate that for the *GROWTH* and *MATURE* stages the impact of cash flow volatility in affecting *IVOL* is reduced, but is still positive for the *GROWTH* stage firms (0.003–0.002 = 0.001) though reduced to zero for *MATURE* stage firms. The *F*-test results suggest that the sum of coefficients (baseline plus interactions) are statistically significant at $p < 0.01$.

We argued in the hypotheses section that *IVOL* reduces for growth and mature stage firms because they are exposed to less uncertain and less volatile future cash flows compared to *SHAKE-OUT* stage firms. Less uncertainty, therefore, dampens the interactive coefficients, namely *GROWTH**SD_CF* and *MATURE**SD_CF*. In sum, regression results largely support our conjecture in H2A that the role of cash flow in affecting *IVOL* varies depending on the firm life cycle stages.

4.3.4. Information uncertainty (analyst forecast dispersion), firm life cycle and IVOL

In Section 2, we hypothesized that information uncertainty induced *IVOL* will vary depending on firm life cycle stages. Table 6 reports regression results, where continuous variables used in the interaction terms are first mean-centered. In Columns (1) and (2), the coefficient on *DISP* is positively and significantly (coefficient = 0.004; $p < 0.01$) associated with *IVOL*. Moreover, the coefficients for life cycle stages suggest that, in comparison with firms in the *SHAKE-OUT* stage (the base case for our regression analysis), firms in the *INTRO* and *DECLINE* (*GROWTH* and *MATURE*) stages are positively (negatively) associated ($p < 0.01$) with IVOL. The interactions of *INTRO* and *DECLINE* with DISP (i.e., *INTRO**DISP* and *DECLINE**DISP*) are insignificant, implying that the forecast dispersion of these stages are no different from the baseline case (*SHAKE-OUT*) in affecting IVOL. Interactive coefficients for *GROWTH**DISP* and *MATURE**DISP* are negative and significant (coefficient = −0.002; $p < 0.05$). These indicate that for *GROWTH* and *MATURE* firms the impact of analyst forecast dispersion in affecting *IVOL* is reduced to 0.002. The *F*-test results suggest that the sum of coefficients (baseline plus interactions) are statistically significant at $p < 0.01$. Thus, the effect of *DISP* in affecting *IVOL* is still positive, but not as strong as in the *SHAKE-OUT* stage. This result is consistent with the argument that growth and mature firms are subject to less dispersion owing to their long existence, better media coverage, stable or promising performance, close monitoring by the analysts and investors and established

Table 6

Information environment, life cycle stages, and IVOL

$$IVOL_{i,t} = \gamma_0 + \sum_{j=1}^{4}\gamma_j LCS_{i,t} + \gamma_5 DISP_{i,t} + \sum_{K=6}^{9}\gamma_k LCS_{i,t} * DISP_{i,t} + \gamma_{10} SIZE_{i,t} + \gamma_{11} LEV_{i,t} + \gamma_{12} MTB_{i,t} + \gamma_{13} ROE_{i,t} + \gamma_{14} DIV_{i,t} + \gamma_{15} SDCF_{i,t} + \gamma_{16} HINDEX_{i,t} + \gamma_{17} AGE_{i,t} + \gamma_{18} RET_{i,t} + \gamma_{19} FRQ_{i,t} + \sum_t \gamma_t \mathrm{YEAR}_t + \sum_t \gamma_t \mathrm{IND}_t + \varepsilon_{i,t} \ldots\ldots(3).$$

Variables	IVOL_CAPM	IVOL_FF3
INTRO	0.005***	0.005***
	[14.21]	[14.59]
GROWTH	−0.001***	−0.001***
	[−4.07]	[−4.36]
MATURE	−0.002***	−0.002***
	[−7.56]	[−7.60]
DECLINE	0.007***	0.007***
	[15.37]	[16.38]
DISP	0.004***	0.004***
	[5.13]	[5.17]
INTRO * DISP	−0.000	−0.000
	[−0.56]	[−0.64]
GROWTH * DISP	−0.002**	−0.002**
	[−2.11]	[−2.10]
MATURE * DISP	−0.002**	−0.002**
	[−2.00]	[−2.31]
DECLINE * DISP	−0.001	−0.001
	[−1.50]	[−1.62]
SIZE	−0.003***	−0.003***
	[−50.72]	[−52.05]
LEV	0.006***	0.005***
	[9.31]	[9.71]
MTB	0.000***	0.000***
	[5.19]	[5.24]
ROE	−0.002***	−0.002***
	[−11.11]	[−12.26]
DIV	−0.003***	−0.003***
	[−13.62]	[−13.61]
SD_CF	0.001**	0.001**
	[2.15]	[2.15]
HINDEX	0.000	0.000
	[0.21]	[0.24]
AGE	−0.002***	−0.002***
	[−19.25]	[−20.04]
RET	0.002***	0.002***
	[12.19]	[14.25]
FRQ	−0.009***	−0.009***
	[−15.43]	[−16.54]
Year FE	Yes	Yes
Industry FE	Yes	Yes
Constant	0.050***	0.050***
	[31.72]	[31.99]
Observations	43,510	43,510
Adj. R^2	0.57	0.60
No of firms	5788	5788

Notes: Variable definitions are provided in the Appendix A. Robust t-statistics in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

reputation (Bentley, Omer, & Twedt, 2013; Diamond & Verrecchia, 1991; Easley & O'hara, 2004; Gompers, 1996; Hasan et al., 2015; Pástor & Veronesi, 2003). Less degree of uncertainty, as reflected in forecast dispersion, dampens the interactive coefficients for the growth and mature stages. These results also signify that the role of forecast dispersion in affecting *IVOL* varies depending on the firm life cycle stages.

4.4. Sensitivity analyses

4.4.1. Alternative benchmark: mature stage

In our main analyses we used the shake-out stage as a benchmark. However, one may argue that the shake-out stage is a transitory one in which firms may make strategic changes causing the IVOL to be ambiguous. To allay this concern, we use the mature stage of a firm life cycle as an alternative benchmark for the analysis. We argue that mature firms have the lowest IVOL owing to their lower cash flow volatility and information uncertainty. Therefore, we expect firms in other stages of their life cycle to be associated with relatively higher IVOL, when the mature stage is used as a benchmark. As expected, in untabulated results we find that firms in the *INTRO* (coefficient = 0.006, $t = 19.87$), *GROWTH* (coefficient = 0.001, $t = 2.78$), *SHAKE-OUT* (coefficient = 0.002, $t = 9.54$) and *DECLINE* stages (coefficient = 0.007, $t = 20.32$) are significantly positively associated with *IVOL_CAPM*. We obtain qualitatively similar results for the *IVOL_FF3* measure.

4.4.2. Alternative life cycle proxy (RE/TA, RE/TE and AGE^2)

As a robustness check, we test the association between firm life cycle and *IVOL* using the alternative life cycle measure of DeAngelo et al. (2006). They argue that firms with high Retained Earnings to Total Assets (*RE/TA*) and Retained Earnings to Total Equity (*RE/TE*) ratios are typically more mature, or old with declining investment; while firms with low *RE/TA* and *RE/TE* ratios tend to be young and growing. Therefore, they argue that *RE/TA* and *RE/TE* are appropriate firm life cycle proxies. The coefficient for *RE/TA* is −0.002 and for *RE/TE* is −0.0003 ($p < 0.001$) for both *IVOL_CAPM* and *IVOL_FF3*. Thus, regression results imply that, compared to young and growing firms, IVOL is significantly lower for mature stage firms (results untabulated).

Some empirical studies use firm age as a proxy for firm life cycle. However, we argue that firm life cycle is non-linear, as a firm can move back and forth in its life cycle (Dickinson, 2011). Therefore, we use a more robust proxy that can capture firms' movement across the life cycle stages (Dickinson, 2011). Nonetheless, to provide additional evidence of the non-linear relation between firm life cycle stage and idiosyncratic volatility, we re-specify the regression model, and include both *AGE* and *AGE*^{2} along with the controls in the regression. Un-tabulated results show that the coefficient for *AGE* is negative and significant ($p < 0.01$) but that for *AGE*^{2} is positive and significant, implying a non-linear relation between the life cycle proxy and IVOL. This provides support for the use of a non-linear life cycle proxy.

4.4.3. Alternative measures of IVOL

In our main analysis, we use the CAPM and Fama-French three-factor models to measure IVOL. In this section, we re-estimate our analysis using both the three-factor Fama and French (1993) model including a momentum factor, as in Carhart (1997), and the five factor Fama and French (2016) models. Results tabulated in Table 7 using *IVOL_FF4* and *IVOL_FF5* corroborate the conclusions from our main analyses. In particular, we continue to find negative and statistically significant ($p < 0.01$) coefficients for the *GROWTH* and *MATURE* life cycle stages, and positive and significant ($p < 0.01$) coefficients for the *INTRO* and *DECLINE* stages, suggesting that the specific measure of IVOL does not drive our main findings.

4.4.4. Inclusion of additional controls

In our main regression analysis, we do not control for institutional shareholdings and stock turnover explicitly, and this may bias the findings of our study, particularly since institutional shareholdings and stock turnover may differ across firms and across life cycles within firms, and relate to both firm life cycle and idiosyncratic risk. To allay this concern, we rerun the regressions after including (i) the percentage of shares held by institutions retrieved from Thomas Reuter's F13 File and (ii) the monthly average stock turnover. Untabulated regression results provide a qualitatively similar conclusion, and the sign and significance of the main variables of interest remain the same.

Table 7
Sensitivity analysis: Alternative measures of IVOL.

Variables	(Model 1) *IVOL_FF4*	(Model 2) *IVOL_FF5*
INTRO	0.003***	0.003***
	[10.60]	[10.26]
GROWTH	−0.002***	−0.002**
	[−7.84]	[−7.81]
MATURE	−0.002***	−0.002***
	[9.36]	[8.68]
DECLINE	0.005***	0.005***
	[13.57]	[13.71]
Other control variables	Yes	Yes
YEAR/IND FE	Yes	Yes
Constant	0.057***	0.056***
	[27.08]	[27.00]
Observations	64,516	64,516
Adj. R^2	0.57	0.58
No of firms	6944	6944

Notes: Variable definitions are provided in the Appendix A. Robust t-statistics in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.4.5. Fama-McBeth regression

As a robustness test, we rerun the regressions using the Fama and MacBeth (1973) cross-sectional regression method. The coefficients on the baseline *INTRO* and *DECLINE* stages are 0.004 (t-statistic 9.34) and 0.006 (t-statistic 18.54), while the coefficients on the baseline *GROWTH* and *MATURE* stages are −0.002 (t-statistic −4.60) and −0.003 (t-statistic −6.13) for the *IVOL_CAPM* measure. The sign and significance on the life cycle stages remain the same even when the *IVOL_FF3* model is used as the proxy for IVOL. Taken together, our untabulated annual cross-sectional regression generally supports the pooled regression results.

5. Conclusion

This paper examines the association between firm life cycle stages and idiosyncratic volatility, and investigates whether the roles of fundamental uncertainty and information uncertainty in affecting idiosyncratic volatility vary depending on firm life cycle stages. Since idiosyncratic volatility has important implications for portfolio management, diversification strategy, managerial compensation policies and valuation of employee stock options (March & Shapira, 1987; Weber, 2004), it is important to understand the causes and consequences of this firm-specific risk. We examine the role of firm life cycle in this process.

Our study is motivated by inconclusive findings in the finance literature that uses an imprecise proxy to relate firm life cycle with idiosyncratic volatility. Both Fink et al. (2010) and Pástor and Veronesi (2003) show that younger firms are associated with higher IVOL than their older counterparts. In contrast, Ferreira and Laux (2007) and Luo and Bhattacharya (2009) find a positive association between age and idiosyncratic volatility, implying that older firms are associated with higher IVOL. These studies not only use an imprecise life cycle proxy, but also consider firm life cycle as a linear progression. We use a finer proxy for firm life cycle stages to test the association between IVOL and firm life cycle stages.

Using a large panel of US data, we document that, compared to the shake-out stage, IVOL is higher for the introduction and decline stages

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of the firm life cycle, while it is lower for the growth and maturity stages. We also show that the role of cash flow volatility in affecting IVOL attenuates during the growth and mature stages. Finally, we document that the role of informational uncertainty in affecting IVOL differs based on a firm's stage in its life cycle. Our study contributes to the area of literature on the determinants of IVOL. We also contribute to the life cycle literature by showing the unique role of firm life cycle in explaining cross-sectional variation in IVOL.

Appendix A. Variable definition and measurement

Variables	=	Definition and measurement
Dependent variable		
IVOL_CAPM		Idiosyncratic volatility estimated from CAPM model
IVOL_FF3		Idiosyncratic volatility estimated from Fama and French (1993) model
Firm life cycle proxies		
LCS		A vector of dummy variables that capture firms' different stages in the life cycle
RE/TA		Retained earnings (*RE*) as a proportion of total assets (*AT*)
RE/TE		Retained earnings (*RE*) as a proportion of total equity (*CEQ*)
		Fundamental uncertainty and information environment proxies
SD_CF		Standard deviation of cash flow, measured as the rolling standard deviation of cash flow from operation (*OANCF*) scaled by total assets (*AT*) over the previous three years
DISP		*DISP* is the dispersion in forecasts immediately before the end of the fiscal year and is scaled by the price at the end of the previous year. We require at least three analyst forecasts to compute forecast dispersion.
Control variables		
SIZE		Natural logarithm of market value of equity (*PRCC_F* * *CSHO*)
LEV		Leverage, measured as total long-term debt (*DLTT*) scaled by total asset (*AT*)
MTB		Market-to-book ratio, measured as market value of equity (*PRCC_F* * *CSHO*) scaled by book value of equity (*CEQ*)
ROE		Return on equity, measured as income before tax and extraordinary items (*PI* – *XI*) scaled by total equity (*CEQ*)
DIV		Dividend payout ratio, measured as dividend to common stock (*DVC*) scaled by operating income (*PI* - *XI*). We replace missing values of dividend to common stock with 0.
HINDEX		Herfindahl index, a measure of competition among firms in the industry
AGE		Age is measured as the number of years since the firm was first covered by the Center for Research in Securities Prices (CRSP) (*DATADATE* – *BEGDAT*). For regression analysis, we measure AGE as natural log of (1 + age of the firm).
AGE_FND		Age is measured as the number of years since the firm was founded (Loughran & Ritter, 2004). For regression analysis, we measure *AGE* as natural log of (1 + age of the firm).
RET		Yearly stock return
FRQ		Financial reporting quality, estimated by the performance-matched discretionary accruals (*DAC*) model developed by Kothari, Leone, and Wasley (2005). In the correlation and regression analysis, we multiply the absolute *FRQ* by −1, so that a higher value indicates better financial reporting quality.
Year		Dummy variables to control for fiscal year effect
IND		Dummy variables to control for industry effect

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