Firm Life Cycle, Expectation Errors and Future Stock Returns

Theodosia Konstantinidi*

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ABSTRACT

I study the return predictability of firm life cycle, originally documented by Dickinson (2011). I show that a hedge portfolio strategy going long on mature firms and short on introduction firms generates a significant hedge portfolio return of 1.29% per month in return-weighted portfolios and 0.72% in value-weighted portfolios. The returns to firm life cycle are related to investors' and analysts' expectation errors, are driven by market-wide investor sentiment, and are more pronounced among stocks with low institutional ownership and high idiosyncratic volatility. Quantile regressions show that introduction firms have considerably greater uncertainty and skewness in future earnings growth outcomes than mature firms, such that analysts are better able to justify optimistically biased forecasts for introduction firms compared to mature firms.

JEL classification: G12; G14.

Keywords: Firm life cycle, Stock returns, Expectation errors, Limits to arbitrage.

* Theodosia Konstantinidi is from Bayes Business School (formerly Cass), City, University of London, 106 Bunhill Row, London, EC1Y 8TZ, United Kingdom (sonia.konstantinidi.1@city.ac.uk). I appreciate helpful comments from Mary Barth, Mark Bradshaw, Andrey Golubov, Cristina Grande and Xing Huan. I am also grateful to Tim Martens for his guidance on patent data.

1. Introduction

Firm life cycle is a key input to equity valuation, because it conveys information about future dividends (DeAngelo et al., 2006), future earnings (Dickinson, 2011; Vorst and Yohn, 2018) and growth (Vorst and Yohn, 2018). Firm life cycle has also been shown to predict future stock returns (Dickinson, 2011). The attention that firm life cycle has attracted in the literature provides scope for further applications of firm life cycle measures in the context of equity valuation. The validity of such applications, however, depends on the extent to which investors rationally incorporate firm life cycle information into stock prices.[1] The purpose of this paper is to evaluate this important condition.

My baseline results reinforce prior evidence that firm life cycle is a strong predictor of future stock returns. Over the period 1989–2019, a hedge portfolio strategy going long on mature firms and short on introduction firms generates an average return of 1.29% per month in return-weighted portfolios (RW) and 0.72% per month in value-weighted (VW) portfolios. Firm life cycle continues to predict future stock returns after controlling for numerous firm-level characteristics.

A mispricing explanation for the firm life cycle effect would contend that investors produce systematically optimistic and pessimistic expectations for introduction and mature firms, respectively. Under this view, the returns to firm life cycle reflect the reversal of expectation errors and must occur largely around earnings announcement dates. Consistent with mispricing, I find a strong association between firm life cycle and earnings announcement returns in the four quarters subsequent to portfolio formation. Specifically, introduction firms exhibit negative earnings announcement returns, while mature firms exhibit positive earnings announcement returns. In addition, the returns of introduction (mature) firms are significantly lower (higher) on information days compared to non-information days.

I complement the above analysis using earnings forecast data on sell-side analysts. Specifically, I examine whether sell-side analysts make the type of mistakes that are consistent with the return predictability of firm life cycle. The results show that analysts' forecast errors, measured ex-post, are large and negative for firms in the introduction phase, while they are small and significantly less negative for firms in the mature phase. One interpretation of these results is that analysts lack the sophistication to understand the ability of firm life cycle to predict future

[1] A natural application of firm life cycle is the identification of peers in the context of multiples-based valuation. If investors overvalue (undervalue) introduction (mature) firms, valuation multiples will be over (under) estimated.

earnings. Alternatively, it is possible that analysts are better able to justify optimistically biased forecasts for introduction firms compared to mature firms. Quantile regressions show results consistent with the latter; introduction firms have considerably greater uncertainty and skewness in future earnings growth outcomes than mature firms, which enables analysts to support a biased conclusion and carry favour with managers.[2] Regardless of the interpretation, the implication remains the same; professional investment intermediaries fail to inform investors about the forecast implications of firm life cycle, corroborating the hypothesis of investors' irrational expectations.

Next, I explore the possibility that sentiment-driven investors may be driving the return predictability of firm life cycle. Baker and Wurgler (2006, 2007) provide evidence that high sentiment is associated with overvaluation, whereas low sentiment is associated with undervaluation. If the firm life cycle effect reflects market mispricing, it should be stronger following periods of high sentiment, consistent with short-sale impediments making overpricing more prevalent than underpricing (Miller, 1977; Stambaugh et al., 2012). In addition, the returns to the short leg of the strategy should be lower following periods of high sentiment. Using the market-wide sentiment index constructed by Baker and Wurgler (2006), I find results which are consistent with expectations. Following periods of high sentiment, introduction firms earn significantly lower returns and the long-short return spread is substantially larger, compared to periods of low sentiment.

Finally, I discuss the role of limits to arbitrage in the pricing of firm life cycle. The typical argument against mispricing is that it should be eliminated by rational traders looking to exploit investment opportunities. If, however, rational traders cannot fully exploit such opportunities, mispricing will remain. I look at two types of limits to arbitrage: short-sale constraints and idiosyncratic risk.

Following Nagel (2005), I use institutional ownership to proxy for the risk of short selling. Institutional ownership is known to increase the supply of lendable shares, thereby reducing borrowing costs (D'Avolio, 2002). I show that the performance of the firm life cycle strategy is significantly more pronounced among stocks characterized by low institutional ownership. Following Pontiff (1996) and Wurgler and Zhuravskaya (2002), I also use the idiosyncratic portion

[2] See Bradshaw, Lee and Peterson (2016) for an extensive analysis on the interaction between analysts' incentives for optimism and forecast difficulty.

of a stock's volatility as a second proxy for arbitrage risk. Here again, I show that firm life cycle return predictability becomes stronger in the presence of high idiosyncratic volatility. Hence, limits to arbitrage is a plausible reason why the returns related to firm life cycle are sustained over time.

The paper contributes to the literature in three main ways. First, it complements and reinforces evidence in Dickinson (2011) by showing that the firm life cycle return predictability is not subsumed by existing stock return predictors. Second, it shows evidence that the returns to firm life cycle reflect reversals of expectation errors, which are more likely to occur following periods of high sentiment and among stocks subject to limits to arbitrage. Third, the paper generates insights into the usefulness of sell-side analysts' forecasts. Specifically, it shows that financial analysts produce optimistically biased forecasts for introduction firms – firms that are characterized by high uncertainty and skewness in future earnings growth. Taken together, the findings of this paper echo Penman (2011)'s fundamentalist dictum "Beware of paying too much for growth".

The rest of the paper is organized as follows. In Section 2, I discuss the firm life cycle construct and the related literature. In Section 3, I describe the sample selection process and provide summary statistics for the five firm life cycle stages. In Section 4, I present my empirical results. In Section 5, I conclude the paper.

2. Firm life cycle and related literature

Gort and Klepper (1982) hypothesize five life cycle stages for a product innovation, based on the number of producers: (1) Introduction, where a product innovation is just introduced into the market and the number of producers is low; (2) growth, where the number of producers grows dramatically and net entry is positive and increasing; (3) Mature, where exits increase due to price competition and the number of entrants roughly equal the number of exits; (4) Shake-out, where the number of producers starts declining and net entry is negative; (5) Decline, a period of zero net entry where the product becomes finally obsolete.

Measuring life cycle at the firm-level is a difficult task to undertake. Firms can introduce multiple product innovations over their life and they can operate in multiple industries. As a result, a firm's life cycle stage becomes a combination of overlapping product life cycle stages which are difficult to aggregate in a single measure (Dickinson, 2011). A substantial amount of prior literature utilizes continuous variables to capture firm life cycle – namely, payout ratio, age, sales growth and retained earnings (Anthony and Ramesh, 1992; DeAngelo et al., 2006; Koh et al., 2015). Arguably, the association between these proxies and firm life cycle is unlikely to be linear, and hence, sorts on these metrics can result in inaccurate life cycle classifications.

In this regard, Dickinson (2011) develops a new measure of firm life cycle, which allows for non-monotonic and non-sequential progression through a firm's life. It is shown to be consistent with economic theory and to outweigh competing life cycle classification schemes. The proposed life cycle proxy exploits the nature of operating, investing and financing cash flows under different life cycle stages. Specifically, it uses the *signs* of the three types of (net) cash flows to produce eight combinations of cash flow patterns. The eight combinations are subsequently reduced to the five theoretical life cycle stages: introduction, growth, mature, shake-out, and decline, as shown in Table 1.

[Please Insert Table 1 about Here]

Evidence so far suggests that firm life cycle, measured from cash flow patterns, is an important input to earnings forecasting and equity valuation. Specifically, firm life cycle is shown to identify differential persistence in profitability and to predict future stock returns (Dickinson, 2011). It is also shown to increase the out-of-sample accuracy of profitability and growth forecasts (Vorst and Yohn, 2018) and to be associated with the level of investment in organizational capital (Hasan and Cheung, 2018). In light of this evidence, one would expect further applications of firm life cycle measures in the context of equity valuation. The validity of such applications, however, is likely to depend on whether investors rationally impound firm life cycle information into stock prices. The aim of this paper is to provide insights into this condition.

3. Sample and Data

My main data source is the intersection of CRSP and Compustat databases over the period 1989–2019. The beginning of the sample period reflects the availability of cash flow data, which are necessary to construct the Dickinson (2011) firm life cycle proxy. I restrict the sample to common stocks (CRSP share codes 10 and 11) listed on NYSE, Amex, or Nasdaq (CRSP exchange codes 1, 2 and 3). Following Dickinson (2011), I exclude financial firms (SIC codes in the range 6000–6999) because their structure of cash flows is materially different compared to other industries. I also exclude stocks with market value of equity less than $10 million, to avoid the influence of small stocks. In subsequent analysis, I supplement my main dataset with additional variables from I/B/E/S (earnings per share forecasts and actuals), the website of Jeffrey Wurgler (investor sentiment data)[3], and Thomson Reuters 13f Holdings (institutional ownership). Detailed definitions of all variables are provided in the Appendix.

Panel A of Table 2 presents details of the sample selection process, which results in a sample of 107,049 firm-year observations. Panel B reports frequencies of the five life cycle stages, showing that the majority of the sample consists of mature (37.38% of the sample) and growth firms (30.28% of the sample). Introduction, shake-out and decline firms comprise only 17.23%, 8.13% and 6.98% of the sample, respectively, suggesting that firms tend to stay in the mature and growth phases for a longer period of time compared to other life cycle stages.

Panel C of Table 2 reports associations between firm characteristics and firm life cycle stages.[4] Consistent with expectations, age (*Age*) and market capitalization (*ME*) are maximized at maturity, whereas growth (as captured by asset growth (*AGR*), accruals (*ACC*) and book-to-market (*BM*)) is maximized at the introduction phase. The associations between firm characteristics and firm life cycle stages are non-linear, in line with the results in Dickinson (2011).

[Please Insert Table 2 about Here]

Figure 1 illustrates the annual frequency of each firm life cycle stage over the period 1989–2018. In most years, the mature phase retains the greatest percentage, while the decline phase exhibits the lowest percentage. Notably, the percentage of firms in the growth phase has dropped over the sample period by 11.42%, while the percentage of firms in the mature phase has increased by 5.22%.

[Please Insert Figure 1 about Here]

4. Results

4.1. Portfolio sorts

I begin my empirical analysis with portfolio sorts based on firm life cycle. In all tests, I require a three-month lag for cash flow information to become publicly available. Portfolios are rebalanced monthly. That is, on the 31st of January of year *t*, portfolio formation involves firms with fiscal year-ends from November of year *t-2* to October of year *t-1*.[5] Following Asparouhova

[3] Investor sentiment data are available for the period 1965-2018 at https://pages.stern.nyu.edu/~jwurgler/.
[4] Missing capitalized R&D is set to zero. All variables are winsorized at the top and bottom 1% of their distribution.
[5] Inferences remain the same if I use a six-month lag instead.

et al. (2013), I use prior-period gross (one-plus) return-weighted (RW) and value-weighted (VW) portfolios. Both approaches effectively eliminate the return biases that arise in equally-weighted portfolios due to microstructure noise.[6] When a firm delists, I use the delisting return in the delisting month. If a delisting is due to liquidation (delisting codes 500 or between 520 and 584) and the delisting return is missing, the delisting return is set to -30% for NYSE/AMEX firms (Shumway, 1997) and -55% for NASDAQ firms (Shumway and Warther, 1999). Table 3 presents the results.

Panel A reports average monthly raw returns for five portfolios formed on the basis of firm life cycle. Under both RW and VW weighting schemes, mature firms outperform introduction firms in the next month, consistent with Dickinson (2011). A hedge portfolio strategy going long on mature firms and short on introduction firms results in a significant RW hedge portfolio return equal to 1.29%. The corresponding VW hedge portfolio return is equal to 0.72%, also statistically significant.

Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors – the excess market return, SMB and HML. Using RW portfolios, I find a negative abnormal return for introduction firms (-0.97%) and a positive abnormal return for mature firms (0.51%). The abnormal return of the hedge portfolio (mature – introduction) is equal to 1.47% and is statistically significant. Inferences remain the same when using VW portfolios. That is, mature firms earn a premium compared to introduction firms, and this premium is largely unexplained by the market return, HML and SMB.[7]

[Please Insert Table 3 about Here]

Figure 2 provides a graphical view of the results in Table 3 using RW portfolio returns. Panel A plots the cumulative performance of the five firm life cycle portfolios and Panel B plots the cumulative performance of the hedge portfolio strategy. The figure confirms that both introduction and mature firms contribute to the significant hedge portfolio return, while it is evident that the returns of mature firms exhibit less volatility. Figure 3 provides the same plots using VW portfolio returns. The cumulative performance of the hedge portfolios strategy largely mimics the one

[6] Value-weighting reduces the influence of small stocks where mispricing is known to be larger. For the purpose of this paper, average returns on an equal, return-weighted basis (as opposed to value-weighted basis) may be more informative (see Asparouhova et al., 2013 for a related discussion).

[7] Results are robust when alphas are computed against the five Fama and French (2015) factors and the Hou et al. (2015) *q*-factors (see Table OA-2 of the online appendix).

obtained from RW portfolios until the year 2009, although overall it results in lower wealth accumulation. This finding is not surprising, given that mispricing is known to be concentrated among small stocks which are deprioritized in VW portfolios.

[Please Insert Figures 2 and 3 about Here]

4.2. Firm-level return regressions

I perform Fama-MacBeth regressions of future monthly stock returns on the five firm life cycle stages and a set of other firm characteristics. *Introduction*, *Growth*, *Mature*, *Shake-Out* and *Decline* are dummy variables that take the value of 1 if the firm belongs to the corresponding life cycle stage and 0 otherwise. To correct for the bias in the regression coefficient estimates arising from microstructure noise, I weigh the estimation by prior period gross (one-plus) returns (RW) (Asparouhova et al., 2013). To ease interpretation, I standardize all of the control variables to zero mean and one standard deviation.[8] The estimation results are presented in Table 4.

Column 1 reports results from regressing future stock returns on the five firm life cycle stages, confirming the portfolio sort results: Mature firms earn on average higher returns than introduction firms (1.26% versus -0.03% per month), and the difference is on average 1.29% per month and statistically significant. Column 2 repeats the regression after controlling for additional firm-level characteristics, namely, the number of years on CRSP (*age*), book-to-market (*logBM*), market capitalization (*logME*), market beta (β), idiosyncratic return volatility (*IdioRisk*), illiquidity (*Illiquidity*), momentum (Ret^{-2-12}), reversal (Ret^{-1}), asset growth (*AGR*), operating profitability (*OP*) and accruals (*ACC*)[9]. The main result remains unchanged; mature firms continue to outperform introduction firms in the subsequent month. The added controls exhibit associations with future returns that are in line with prior research: market value of equity (Banz, 1981), idiosyncratic volatility (Ang et al. 2006), prior-month returns (Jegadeesh, 1990), asset growth (Titman et al., 2004; Cooper et al., 2008) and accruals (Sloan, 1996) are negatively associated with future stock returns; in contrast, book-to-market (Stattman, 1980; Rosenberg et al., 1985), momentum (Jegadeesh and Titman, 1993) and gross profitability (Novy-Marx, 2013) are

[8] Accordingly, *Introduction*, *Growth*, *Mature*, *Shake-Out* and *Decline* capture the average (monthly) future stock return of a firm in the corresponding life cycle stage when all independent variables are at their *mean* level.

[9] Controlling for accruals alongside operating profitability implicitly controls for cash-based operating profitability (see Ball et al., 2016).

positively related to future stock returns. Age and market beta exhibit no return predictability.[10] Column 3 adds to the same regression three innovation-related return predictors – R&D intensity (*R&D*), patent intensity (*Patent*) and patent citation impact (*Citation*). Here again, mature firms continue to outperform significantly introduction firms. Consistent with prior literature, R&D intensity, patent intensity and patent citation impact exhibit a positive association with future stock returns (Chan et al., 2001; Deng et al., 1999; Hirshleifer et al., 2013).

[Please Insert Table 4 about Here]

Overall, my evidence reinforces evidence in Dickinson (2011) that firm life cycle exhibits stock return predictability. Moreover, this predictability survives a number of control variables that are associated with future stock returns. The subsequent tests aim to shed light on the mispricing explanation for this effect.

4.3. Earnings announcement returns

If introduction and mature firms are mispriced, subsequent price corrections should occur around earnings announcements dates, when new information is released to the market (Bernard and Thomas, 1990; Bernard et al., 1997). This is what I examine in this section. The same hypothesis has been tested by Sloan (1996) for the accrual effect, by La Porta et al. (1997) for the value effect and by Engelberg et al. (2018) for 97 stock return anomalies.

I obtain earnings announcement dates from the Compustat quarterly database. I then measure market-adjusted returns over the windows [-1, +1], [-3, +3] and [-5, +5] centered on the firms' quarterly earnings announcement dates.[11] For each event window, I aggregate earnings announcement returns related to the four quarters following fiscal year-end.[12] Panel A of Table 5 presents the results. I find that introduction firms exhibit negative excess returns around subsequent earnings announcement dates, while mature firms exhibit positive excess returns. This result holds under all three event windows. The difference in the earnings announcement returns

[10] I also report *value*-weighted Fama-MacBeth regressions in Table OA-1 of the online appendix and find consistent results.

[11] I use market-adjusted earnings announcement returns, consistent with prior literature (La Porta, 1996; Bernard et al., 1997). Results are robust when I use the market model or the Fama and French (1993) three factor model to compute excess earnings announcement returns (see Table OA-9 of the online appendix).

[12] For a firm with fiscal year end in December 2017, I look at earnings announcement dates that relate to quarters 03/18, 06/18, 09/18 and 12/18. Similarly, for a firm with fiscal year end in June 2018, I look at earnings announcement dates for the quarters 09/18, 12/18, 03/19 and 06/19.

between mature and introduction firms is equal to 3.6% for the [-1, +1] window, 4.8% for the [-3, +3] window, and 5.3% for the [-5, +5] window. These magnitudes comprise 28%, 38% and 42%, respectively, of the total annual market-adjusted hedge return of 12.7% (untabulated), and are consistent with systematic biased expectations across introduction and mature portfolios.[13]

In a subsequent test, I estimate the following regression equation, as in Engelberg et al. (2018):

$$R_{it} = \sum_{j=1}^{5} a_j Firm\ Life\ Cycle_{it}^{j} + \sum_{j=1}^{5} \beta_j Firm\ Life\ Cycle_{it}^{j} \times Eday_{i,t} \sum_{k} \gamma_\kappa\, Control_{it}^{k} + \varepsilon_{it} \qquad (1)$$

R_{it} is the daily return of stock i on day t. $Firm\ Life\ Cycle_{it}^{j}$ is a dummy variable taking the value of one if firm i belongs to a certain life cycle stage on day t, and zero otherwise – it is denoted as *Introduction*, *Growth*, *Mature*, *Shake-Out* and *Decline* for j = 1, 2, 3, 4 and 5 respectively. $Eday_{it}$ is a dummy variable equal to one on earnings announcement days for firm i and zero otherwise. Firm life cycle is defined at the beginning of each month and remains the same throughout the month. Interaction terms indicate whether portfolio returns are higher on earnings announcement days. The control variables – standardized to zero mean and one standard deviation – include 10 lagged values of the daily return, 10 lagged values of the daily squared return, 10 lagged values of the daily trading volume and all of the controls of Table 4 (unreported for brevity). Day fixed effects are also included[14] and standard errors are clustered by firm and day.

Panel B of Table 5 reports the results. In columns 1 and 2, $Eday$ is defined based on the [-1, +1] earnings announcement window. In column 1, the coefficient on $Introduction \times Eday$ is –0.179, suggesting that introduction firms earn returns which are 459% (0.179/0.039 × 100) lower on earnings announcement days. In contrast, the coefficient on $Mature \times Eday$ is positive and equal to 0.096, suggesting that mature firms earn returns which are 114% (0.096/0.084 × 100) higher on earnings news days. Adding the control variables in column 2 leaves the results virtually unchanged. In columns 3 and 4, $Eday$ is defined based on the [-3, +3] earnings announcement window, and in columns 5 and 6, $Eday$ is defined based on the [-5, +5] window. The results are

[13] If returns were evenly distributed across trading days, one would expect to observe approximately 5% (3×4qrts/252 trading days), 11% (7×4qrts/252 trading days) and 17% (11×4qrts/252 trading days) of the annual return to accrue during the three-day, seven-day and eleven-day earnings announcement windows, respectively.
[14] Including day fixed effects in the model ensures that returns are compared across stocks (with and without earnings releases) *on the same day*. Hence, any increases (decreases) in the returns of mature (introduction) firms on earnings days cannot be due to a positive change in risk premia whereby mature (introduction) firms have high (low) betas.

similar, though the magnitudes are smaller due to the greater length of the announcement windows. The signs and the significance of the coefficients are exactly the same.

Overall, the evidence in this section suggests that the life cycle portfolio returns are elevated on days when earnings information is released. This inference is most consistent with a mispricing explanation for the firm life cycle return predictability, though it relies on the assumption that stock returns represent a reliable proxy for investors' revisions in expectations. This assumption is not necessarily valid, considering that stock returns are a function of earnings news, discount rate news, and expected returns. Utilizing a direct measure of earnings expectations should provide further assurance for the validity of the above interpretation. This is what I attempt to do next.

[Please Insert Table 5 about Here]

4.4. Analysts' forecast errors

I investigate whether sell-side analysts' earnings forecasts incorporate the implications of firm life cycle for future earnings. If that is the case, there should be no association between current year's firm life cycle and next year's analysts' forecast errors. The benefit of this test is that it relies on direct measures of earnings forecasts from analysts, which are known to influence investors' expectations. The limitation of this approach, however, is that analysts' forecasts are only available for a set of large firms. Analysts' forecast errors have been used in prior studies to test rational expectations with respect to accruals (Bradshaw et al., 2001) and book-to-market (Doukas et al., 2002).

I use the unadjusted IBES Summary file to obtain the mean consensus forecast of annual earnings per share. I also use the adjusted IBES Summary file to obtain the stock split adjusted actual earnings per share, which I unadjust as of the forecast date. Forecast Error is defined as the actual minus the forecasted earnings per share divided by assets per share.[15] Total assets are obtained from Compustat at the fiscal year-end preceding the forecast date, and shares outstanding are obtained from CRSP as of the forecast date. I implement two tests: the first uses analysts' forecast errors obtained *three* months after fiscal year-end (i.e. March 31 for a December fiscal year-end firm); the second tracks analysts' forecast errors from the month after financial results

[15] Results are robust if I scale the forecast error with the latest actual |EPS|.

are released for 11 months up to the announcement of next year's earnings. The results are reported in Table 6.

Panel A reports mean signed forecast errors for five portfolios formed on the basis of firm life cycle. The mean forecast error is negative across all portfolios, consistent with analysts being on average optimistic (Francis and Philbrick, 1993). Noticeably, the analysts' forecast error is significantly lower for introduction firms (-0.039) compared to mature firms (-0.008), and the difference is highly statistically significant.

Panel B presents mean signed analysts' forecast errors for all firms, introduction firms and mature firms, over the 11 months following the current earnings announcement date and leading up to the next year's earnings announcement date. I stop tracking forecast errors after 11 months, because most firms have announced their next year's earnings by then. Analysts' forecast errors are consistently negative across all months, once again confirming the average optimism in analysts' earnings forecasts. This optimism gradually reduces over time, consistent with the analyst forecasts' walkdown towards beatable targets (Richardson et al., 2004). The mean forecast error is consistently lower for introduction firms compared to mature firms across all months, mirroring the predictable pattern in future stock returns. In month 1, the forecast error is equal to -0.044 for introduction firms versus -0.008 for mature firms, and the difference of 0.036 is statistically significant. This difference monotonically decreases over the next 11 months, reaching the level of 0.014 in month 11, which is also statistically significant.

[Please Insert Table 6 about Here]

The results in Panel B of Table 6 are graphically presented in Figure 4. The plot shows that analysts consistently experience more negative earnings surprises for introduction firms and less negative earnings surprises for mature firms compared to the sample average. The graph also illustrates the monotonic reduction in the forecast error differences between introduction and mature firms over the course of the year.

Collectively, the results suggest that analysts' earnings forecasts do not fully incorporate the implications of firm life cycle for future earnings. They are also consistent with analysts correcting themselves over the course of the year, as new information becomes available through quarterly earnings releases. To the extent that analysts' forecasts influence investors' expectations, these results strengthen the interpretation that the returns to firm life cycle derive from systematic pricing errors.

Bradshaw et al. (2016) show evidence that forecasting difficulty interacts with analysts' incentives to produce optimistic bias and forecast errors' walkdown. They propose that higher forecasting difficulty results in a wider range of possible future outcomes, from which analysts can justify optimistically biased forecasts. If introduction firms have greater forecast uncertainty than mature firms, the observed analysts' forecast bias could be the result of rational behaviour.[16] I provide insights into this possibility in the section below.

[Please Insert Figure 4 about Here]

4.5. Firm life cycle and forecast uncertainty

I use the quantile regression approach to estimate the shape of the distribution of future earnings growth (*EGR*) for firms in the introduction, growth, mature, shake-out, and decline phases. This approach allows me to directly measure the range of possible future earnings outcomes that Bradshaw et al. (2016) refer to, while avoiding the limitations of firm-specific AR(1) regression estimations.[17]

Specifically, I estimate the following model using year by year quantile and OLS regressions (i.e. Fama-MacBeth style).

$$EGR_{it+1} = \sum_{j=1}^{5} a_j Firm\ Life\ Cycle_{it}^{j} + \varepsilon_{it} \tag{2}$$

EGR_{it+1} is the percentage change in earnings for firm *i* in year *t+1*. $Firm\ Life\ Cycle_{it}^{j}$ is a dummy variable taking the value of one if firm *i* belongs to a certain life cycle stage in year *t*, and zero otherwise; it is denoted as *Introduction*, *Growth*, *Mature*, *Shake-Out* and *Decline* for j = 1, 2, 3, 4 and 5 respectively.

I use $Q_{i\tau} = Q_{i\tau}(EGR_{it+1}|Firm\ Life\ Cycle_{it}^{j})$ to denote the estimated conditional τ'th quantile of earnings growth for firm *i* in year *t+1*. I then define earnings uncertainty (IQR_i) as $Q_{i90} - Q_{i10}$, and earnings skewness ($SKEW_i$) as $(Q_{i90} + Q_{i10} - 2 \times Q_{i50})/IQR_i$, similar to Konstantinidi and Pope (2016). I report results for nine quantiles in the set $\tau \in$ {0.05, 0.10, 0.25, 0.40, 0.50, 0.60, 0.75,

[16] I use the terms forecast uncertainty and forecast difficulty interchangeably.

[17] I measure earnings growth as (Gross profit$_t$ – Gross profit$_{t-1}$)/|Gross profit$_{t-1}$|. The further down one looks at the income statement, the more distorted profitability measures become. This is because investments (such as advertising, marketing and R&D) are treated as expenses, even though they may be associated with high economic profits. Gross profit is therefore a cleaner measure of true economic profitability (Novy-Marx, 2013). I winsorize earnings growth at the top and bottom 1% of its distribution.

0.90, 0.95}. Coefficients in quantile regressions are obtained by minimizing the sum of weighted absolute residuals, where the weight is equal to the estimated quantile τ for positive residuals, and $1 - \tau$ for negative residuals. Goodness of fit measures are computed as follows:

$$Pseudo\ R2 = 1 - \frac{Sum\ of\ Weighted\ Absolute\ Residuals\ under\ the\ model\ of\ interest}{Sum\ of\ Weighted\ Absolute\ Residuals\ from\ an\ intercept\ model} \quad (3)$$

Note that pseudo R2s from quantile regressions are *local* measures of goodness-of-fit that depend on the targeted quantile τ and hence, they are not comparable to the R2 obtained from the OLS regression.

The results are reported in Table 7. They show that firm life cycle significantly predicts future earnings growth and the uncertainty in that growth. For introduction firms, the expected value of earnings growth next year is 27.6%, whereas for mature firms it is only a quarter, 7.4%. The difference in expected earnings growth between introduction and mature companies is 20.2%, which is both economically and statistically significant. A rational investor would therefore be willing to pay a premium for the high expected earnings growth in introduction firms, all else equal.

Earnings growth, however, is highly uncertain. For introduction firms, the predicted value of Q_{90} is 1.341 while the predicted value of Q_{10} is –0.663. That is, there is a 10 percent probability that earnings growth next year will be above 134% and a 10 percent probability that earnings growth next year will be below –66.3%. Earnings growth uncertainty, *IQR*, has a value of 2.004, equal to the difference between the predicted values of Q_{90} and Q_{10}. The quantile estimates for mature firms draw a very different picture; the predicted value of Q_{90} is only 0.299 while the predicted value of Q_{10} is also less extreme, –0.168. *IQR* is equal to 0.466, suggesting that there is considerably less uncertainty about future earnings growth outcomes for mature firms than for introduction firms. The difference in *IQR* among introduction and mature firms (1.538) is statistically and economically significant.

Figure 5 illustrates the quantile regression results by plotting the conditional distribution of earnings growth next year for mature and introduction companies. The figure shows that the distribution of future earnings growth for introduction firms is substantially more dispersed and rightly skewed than the distribution for mature firms. That is, introduction firms have greater uncertainty in future earnings growth outcomes than mature firms, and the upside growth potential considerably exceeds the downside potential.

Taken as a whole, the results are consistent with the conjecture that greater earnings uncertainty for introduction firms allows for greater analysts' optimism, while the reverse is true for mature firms. In addition, the presence of positive skewness for introduction firms generates a wide range of *favourable* earnings outcomes, enabling further the justification of analysts' optimistic forecasts.

To the extent that the market *fixates* on analysts' biased expectations, predictable patterns in analysts' forecast errors should be reflected in stock returns. That is, investors should act optimistically for introduction firms.[18]

[Please Insert Table 7 about Here]

[Please Insert Figure 5 about Here]

4.6. Sentiment and returns

I now explore the possibility that sentiment-driven investors are driving the return predictability of firm life cycle. Prior research has provided predictions about how swings in sentiment should affect market valuations of stocks that are difficult to value. Baker and Wurgler (2006, 2007) provide evidence that high sentiment is associated with overvaluation, especially when stocks are characterized by high valuation uncertainty. Hribar and McInnis (2012) show that high sentiment is associated with analysts' forecast optimism particularly among young and uncertain stocks. Stambaugh et al. (2012) explore a broad set of market anomalies and find that the 'anomalous' hedge portfolio returns are greater following periods of high sentiment – this effect is driven entirely by the short leg of the strategies considered.

I measure market-wide investor sentiment using the 2019 updated version of the monthly sentiment index constructed by Baker and Wurgler (2006).[19] I split the time series into high, medium and low sentiment periods using the previous month's sentiment level. I then show returns

[18] An alternative explanation is that investors have a preference for positive skewness and are willing to accept a negative expected return for a potential large earnings realization (Mitton and Vorkink, 2007). Note that introduction firms have a predicted skewness (SKEW) of 0.232 whereas mature firms have predicted SKEW of only 0.063. Though this explanation is plausible, it is inconsistent with the rest of my results, including the earnings announcement returns, analysts' forecast errors, sentiment and the subsequent limits to arbitrage.

[19] The Baker and Wurgler (2006) market-wide sentiment index is based on the first principal component of five standardized sentiment proxies (the closed-end fund discount, the equity share in total new issues, the IPO volume, the first day return on IPOs and the dividend premium). Each of these proxies has first been orthogonalized with respect to a set of six macroeconomic indicators (https://pages.stern.nyu.edu/~jwurgler/).

of the firm life cycle hedge portfolio strategy, conditional on high/medium/low sentiment. Results are reported in Table 8 and are based on RW portfolios.

Panel A documents that the firm life cycle effect is stronger following periods of high sentiment, consistent with short-sale impediments making overpricing more prevalent than underpricing (Miller, 1977). The hedge portfolio return monotonically increases with sentiment (0.14% vs. 1.01% vs. 2.86% per month for low, medium and high levels of sentiment), while the return of the short leg of the strategy monotonically decreases with sentiment (1.33% vs. 0.11% vs -1.72% per month for low, medium and high levels of sentiment). The long leg of the strategy exhibits returns that are statistically the same across low and high sentiment periods, similar to the findings in Stambaugh et al. (2012). Panel B repeats the same test after controlling for the three Fama and French (1993) factors. The same inferences continue to hold. In addition, none of the conclusions change when I use value-weighted portfolio returns (Table OA-4 of the online appendix).

[Please Insert Table 8 about Here]

A central question however remains; in the presence of sophisticated investors, why are these abnormal returns not arbitraged away? Common explanations for the persistence of market mispricing in capital markets focus on limits to arbitrage, including short sale constraints (Nagel, 2005) and idiosyncratic volatility (Shleifer and Vishny, 1997). If limits to arbitrage is the mechanism by which firm life cycle mispricing persists over time, I should find that the performance of the firm life cycle strategy is more pronounced in securities characterized by limits to arbitrage. This is what I explore next.

4.7. Short-sale constraints

Short sale constraints mainly arise due to the risk associated with short selling. Short sellers must borrow shares from stock lenders and must repay those shares on demand (Dechow et al., 2001). Such practice exposes short-sellers to the risk of repurchasing shorted securities at a loss, if alternative stock lenders cannot be found when needed. This risk, however, decreases for stocks with high institutional ownership, as institutional ownership increases the supply of lendable shares and reduces borrowing costs (D'Avolio, 2002). Therefore, stock return predictability should be more pronounced among stocks with low institutional ownership (Nagel 2005). Consistent with this prediction, prior literature shows that institutional holdings are negatively correlated with the value premium (Nagel, 2005; Ali et al., 2003), the post-earnings announcement drift (Bartov et al., 2000) and the accrual anomaly (Collins et al., 2003). If the return predictability of firm life cycle is due to market mispricing, I should also find that the predictable stock returns are more pronounced among stocks with low institutional ownership.

Data on institutional holdings are obtained from the Thomson Financial Institutional Holdings (13F) database. I extract the share of institutional ownership for each stock in each quarter. Following Nagel (2005), I orthogonalize institutional ownership (INST) with respect to size, to calculate *residual* institutional ownership. I perform a logit transformation of INST as follows: logit (INST) = log(INST/1-INST), where values of INST below 0.0001 and above 0.0009 are replaced with 0.0001 and 0.0009, respectively. I then regress logit(INST) on log market capitalization and squared log market capitalization. The regressions are run in each quarter, and the residuals comprise residual institutional ownership (RI).

I implement 5 × 3 sorts based on firm life cycle and residual institutional ownership, resulting in 15 portfolios. Table 9 reports the results using RW portfolios. Panel A presents portfolio raw returns. Conditional on low institutional ownership, the long-short firm life cycle strategy produces a stunning monthly return of 1.57%. Conditional on high institutional ownership, the same strategy produces a monthly return that is about three times less: 0.57% and statistically significant. Notably, this difference is largely driven by the short leg of the strategy – stocks for which short sale constraints are binding. Panel B presents similar patterns using abnormal returns relative to the Fama and French (1993) three factors, with differences in returns being further magnified. The firm life cycle strategy return falls from 1.84% per month to 0.69% per month when moving from low to high institutional ownership tertiles.

When using VW portfolios, I split the sample into small and big stocks. VW portfolios place a greater weight on large cap stocks – stocks for which shorting is available irrespective of institutional ownership (Nagel 2005; Golubov and Konstantinidi, 2019). Hence, VW portfolios are less likely to reveal the interaction effect between firm life cycle return predictability and institutional ownership. The results are shown in Table OA-6 of the online appendix and are consistent with expectations: the firm life cycle hedge portfolio return is substantially larger when institutional ownership is low and this finding holds only for small stocks. Overall, the results in this section are aligned with the limits to arbitrage hypothesis, whereby the return predictability of firm life cycle increases sharply with lower institutional ownership.

[Please Insert Table 9 about Here]

4.8. Idiosyncratic volatility

Arbitrage is typically undertaken by a few sophisticated and poorly diversified traders, who are concerned about the idiosyncratic risk of their investments (Ali et al., 2003). Therefore, idiosyncratic risk deters arbitrage activity (Shleifer and Vishny, 2003). Consistent with this argument, prior literature shows that idiosyncratic volatility exacerbates the value premium (Ali et al., 2003), the post-earnings announcement drift (Hung et al., 2014) and the accrual anomaly (Mashruwala et al., 2006). In this section, I examine whether idiosyncratic risk can also be a reason why the firm life cycle return predictability persists over time. Table 10 presents the results using RW portfolios.

Once again, I implement 5 × 3 sorts based on firm life cycle and idiosyncratic volatility, resulting in 15 portfolios. Idiosyncratic volatility is measured as the standard deviation of residuals from the time-series market model: $R_{it} = \alpha + \beta R_{Mt} + e_{it}$, where R_{it} is the stock's daily stock return and R_{Mt} is the daily value-weighted market return. The regression is run annually over a period of one year ending three months after the firm's fiscal year-end. Panel A presents portfolio raw returns. Conditional on high idiosyncratic volatility, the firm life cycle hedge portfolio strategy produces a significant return of 1.56% per month which drops down to 0.85% when I condition on low idiosyncratic volatility. Panel B shows a similar pattern across idiosyncratic volatility portfolios, when returns are benchmarked against the Fama and French (1993) three factors. Mature firms outperform introduction firms by 1.60% per month in the high idiosyncratic volatility portfolio, and only by 0.88% in the low idiosyncratic volatility portfolio. I continue to find the same patterns when using VW portfolio returns (Table OA-8 of the online appendix). Overall, the results reinforce the evidence that firm life cycle return predictability is stronger in the presence of arbitrage risk. This is consistent with a market mispricing explanation for the firm life cycle effect, whereby impediments to rational pricing are costly to eliminate.

[Please Insert Table 10 about Here]

5. Conclusion

This paper corroborates previous evidence that firm life cycle is a strong predictor of future stock returns, with mature firms earning on average higher returns than introduction firms. This predictability continues to hold after controlling for numerous firm-level characteristics, suggesting that the effect of firm life cycle in returns is distinct.

Further tests reveal that the returns to firm life cycle are related to investors' and analysts' expectation errors, are driven by market-wide investor sentiment and are concentrated in stocks that are subject to low institutional ownership and high idiosyncratic volatility. Quantile regressions show that introduction firms have considerably greater uncertainty and skewness in future earnings growth outcomes than mature firms, such that analysts are better able to justify optimistically biased forecasts for introduction firms compared to mature firms. In short, the results are consistent with a mispricing explanation for the return predictability of firm life cycle.

Appendix. Variable definitions[20]

Variable name	Definition
Main variables	
CFO	Cash flow from operating activities (*OANCF*)
CFI	Cash flow from investing activities (*IVNCF*)
CFF	Cash flow from financing activities (*FINCF*)
Introduction	A combination of negative CFO, negative CFI and positive CFF
Growth	A combination of positive CFO, negative CFI and positive CFF
Mature	A combination of positive CFO, negative CFI and negative CFF
Shake-Out	A combination of negative CFO, negative CFI and negative CFF or a combination of positive CFO, positive CFI and positive CFF or a combination of positive CFO, positive CFI and negative CFF
Decline	A combination of negative CFO, positive CFI and positive CFF or a combination of negative CFO, positive CFI and negative CFF
TA	Total assets (*AT*)
BE	Book value of common equity (*CEQ*)
EGR	Earnings growth defined as (Gross profit_t – Gross profit_{t-1})/|Gross profit_{t-1}|, where gross profit is equal to revenues (*REVT*) minus cost of goods sold (*COGS*) (Novy-Marx, 2013).
Controls/ Characteristics	
Age	Number of years since the stock first appeared in CRSP, measured three months after fiscal year-end (Table 2 Panel C) or monthly (Table 4).
BM	The book-to-market ratio. Book value is defined as book value of common equity (*CEQ*) at fiscal year-end. Market equity is obtained from CRSP three months after fiscal year-end.
LogBM	The natural logarithm of BM.
ME	The market value of equity obtained from CRSP three months after fiscal year-end.
logME	The natural logarithm of ME.
β	Monthly market beta, estimated by regressing firm-level daily stock returns on the value-weighted CRSP market index. The estimation is done over a window of 12 months. A minimum of 60 daily return observations is required.
IdioRisk	The monthly idiosyncratic volatility of a stock, i.e. the portion of total stock return volatility unexplained by the market. IdioRisk is calculated as the standard deviation of the residuals obtained from the regression used to calculate the market beta over a window of 12 months.

[20] Compustat item labels (*XFP* names) for accounting variables are in parentheses.

Illiquidity	The daily ratio of absolute stock return to its dollar volume, averaged over a window of 12 months, calculated monthly (Amihud, 2002).
OP	Operating profitability defined as gross profitability (*REVT – COGS – XSGA - XINT*) divided by lagged total assets (*AT*) (Fama and French 2015).
AGR	Investment, defined as the percentage change in total assets.
Ret^{-2-12}	Prior buy-and-hold 11-month stock return with a lag of 2 months (-2; -12).
Ret^{-1}	Prior one-month stock return.
ACC	Accruals, measured as Δ(Current assets (ACT)) – Δ(Cash and short-term investments (CHE)) – [Δ(Current liabilities (LCT)) – Δ(Debt in current liabilities (DLC)) – Δ(Income taxes payable (TXP))] – Depreciation (DP), scaled by lagged total assets (Sloan 1996; Ball et al., 2016).
R&D	R&D intensity, measured as capitalized research and development expense (*XRD*) scaled by total assets in the same year. Capitalized R&D is computed as $XRD_t + 0.8\times XRD_{t-1} + 0.6\times XRD_{t-2} + 0.4\times XRD_{t-3} + 0.2\times XRD_{t-4}$ (Chan et al., 2001). If missing, it is set to zero.
Patent	Patent intensity, measured as the number of patents granted to a firm in a particular year scaled by the firm's book value of equity in the same year (Deng et al., 1999).
Citation	Patent citation impact for firm *i* in year *t* is measured as the average *adjusted* number of citations received in year *t* by patents granted to firm *i* in the previous five years (Pandit et al., 2011).[21] The *adjustment* in the number of citations requires deflating each patent's citations by the average number of citations received by all patents of the same subcategory that are granted and cited in the same year.[22] Formally, patent citation impact is measured as follows $$Citation = \left(\sum_{j=1}^{5}\sum_{k=1}^{N_{t-j}} C_{ik}^{t-j}\right)\Big/\sum_{j=1}^{5} N_{t-j}$$ where C_{ik}^{t-j} is the *adjusted* number of citations received in year *t* by patent *k* issued to firm *i* in year *t–j* (*j* = 1, 2, 3, 4, 5) and N_{t-j} is the total number of patents issued to firm i in year *t–j* and are cited in year *t*.[23] Data on patent citations are obtained from PatentsView. Data on patent frequency are obtained from the repository of Kogan et al. (2017). The latter source provides also the linktable that matches patent numbers with CRSP "permnos".
<u>Earnings announcements</u>	
Eday	Earnings day, i.e. a dummy variable equal to one on earnings announcement days and zero otherwise.

[21] For example, patent citation impact for firm *i* in 2020 is the average *adjusted* number of citations received in year 2020 by patents granted to firm *i* in the years 1995 to 1999.
[22] Patent subcategory is based on the patent technology classification system of the US Patent and Trademark Office (USPTO).
[23] This adjustment is used by Hirshleifer et al. (2013) to control for differences in citation propensity across different technological fields, grant years and citing years.

Analysts' forecasts	
Forecast	The (mean) consensus analysts' forecast of earnings per share, divided by total assets per share available at the forecast date.
Actual	The actual earnings per share reported by I/B/E/S, divided by total assets per share available at the forecast date.
Analysts' forecast error	Actual – Forecast
Limits to arbitrage	
IdioRisk	The annual idiosyncratic volatility of a stock, i.e. the portion of total stock return volatility unexplained by the market. IdioRisk is calculated as the standard deviation of the residuals obtained from the regression used to calculate the market beta over a window of 12 months ending three months after fiscal year-end.
RI	Residual institutional ownership obtained two quarters prior to firm life cycle measurement, i.e. one quarter prior fiscal year-end. RI is defined as the residual from the following regression model estimated quarterly: $\log(INST_{it}/(1-INST_{it})) = \alpha + \beta LogSZ_{it} + \gamma(LogSZ_{it})^2$, where INST is institutional ownership and LogSZ is the logarithm of market value of equity. Values of INST below 0.0001 and above 0.9999 are replaced with 0.0001 and 0.9999 respectively (Nagel (2005)). Data are from Thomson 13f Holdings.
Quantile regressions	
$Q_{i\tau}$	$Q_{i\tau}$ denotes the estimated τ'th quantile of earnings growth for firm *i* in year *t+1* conditional on firm life cycle.
IQR_i	$Q_{i90} - Q_{i10}$
$SKEW_i$	$Q_{i90} + Q_{i10} - 2 \times Q_{i50}$

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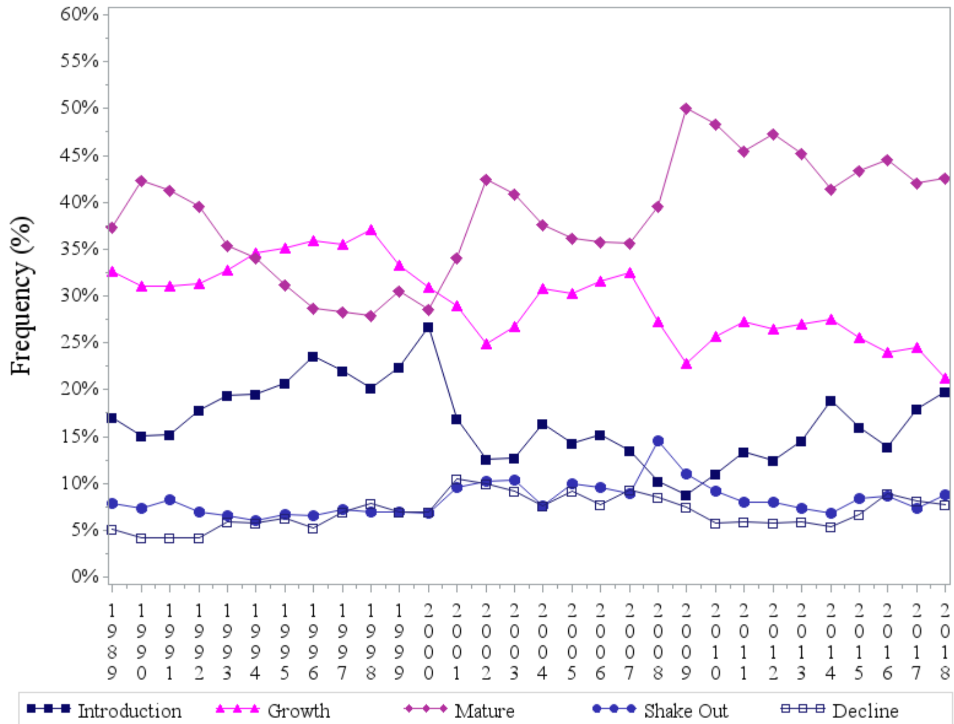
FIGURE 1

Annual frequencies (%) by life cycle stage



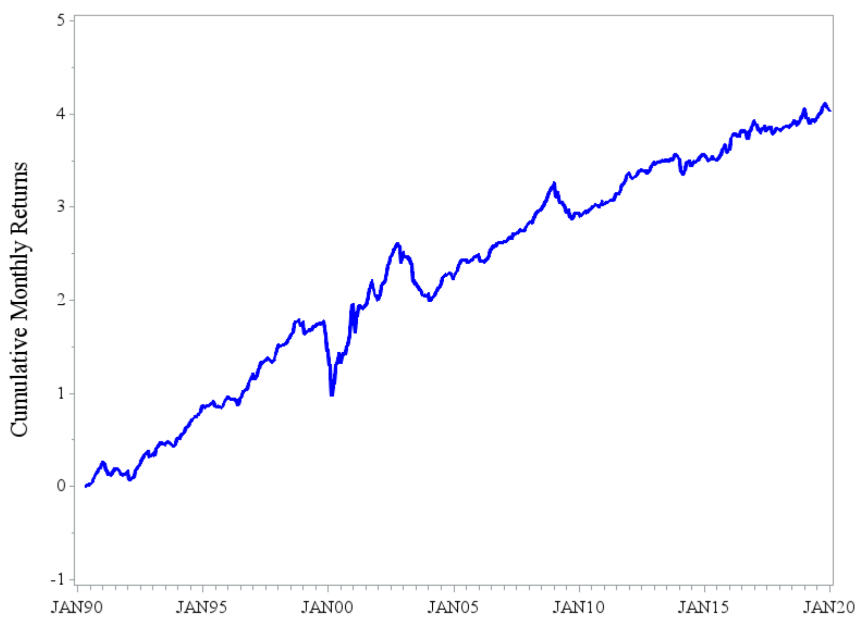
The figure shows yearly frequencies of the five life cycle stages – Introduction, Growth, Mature, Shake-Out, Decline – for the period 1989 to 2018. Firm life cycle stage is measured based on cash flow patterns, as shown in Table 1.

FIGURE 2

Calendar-time cumulative monthly RW portfolio returns

Panel A: Five Life Cycle Stages

Panel B: Hedge Portfolio Strategy



Panel A shows the cumulative performance of five portfolios formed on the basis of firm life cycle. Panel B shows the cumulative performance of the hedge portfolio strategy. Long/short positions are taken in each month on mature/introduction firms, allowing for a three-month lag between fiscal year-end and portfolio formation date. Portfolio returns are prior period gross return-weighted (RW) (Asparouhova et al., 2013). The series illustrate the monthly log of one plus cumulative buy-and-hold return of the corresponding portfolio. The time period runs from April 1990 to December 2019. All variables are defined in the Appendix.

FIGURE 3

Calendar-time cumulative monthly VW portfolio returns

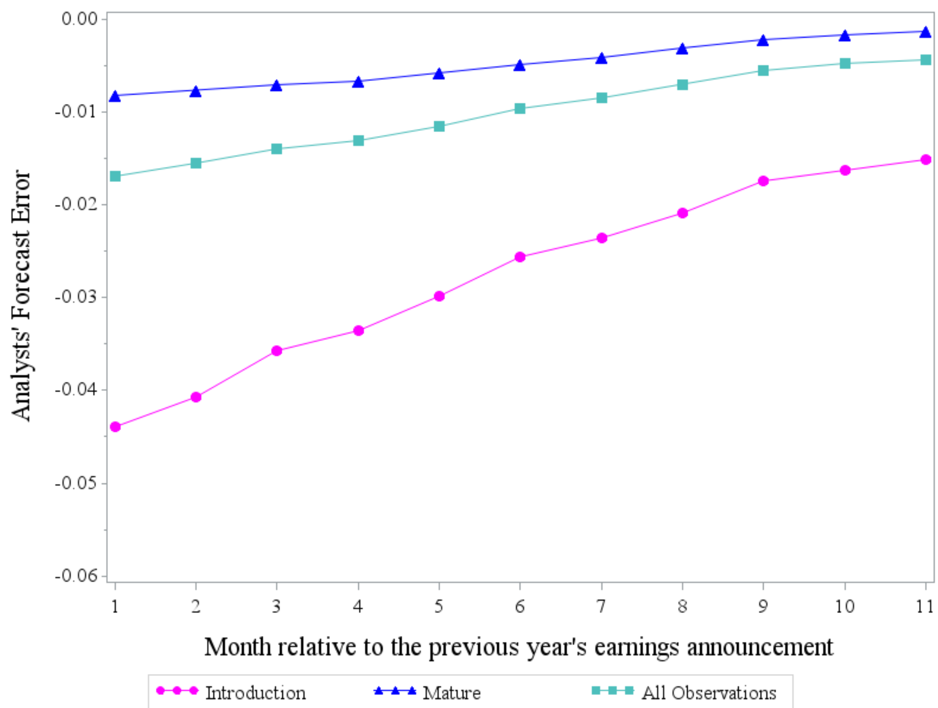
Panel A: Five Life Cycle Stages

Panel B: Hedge Portfolio Strategy

Panel A shows the cumulative performance of five portfolios formed on the basis of firm life cycle. Panel B shows the cumulative performance of the hedge portfolio strategy. Long/short positions are taken in each month on mature/introduction firms, allowing for a three-month lag between fiscal year-end and portfolio formation date. Portfolio returns are value-weighted (VW) (Asparouhova et al., 2013). The series illustrate the monthly log of one plus cumulative buy-and-hold return of the corresponding portfolio. The time period runs from April 1990 to December 2019. All variables are defined in the Appendix.

FIGURE 4

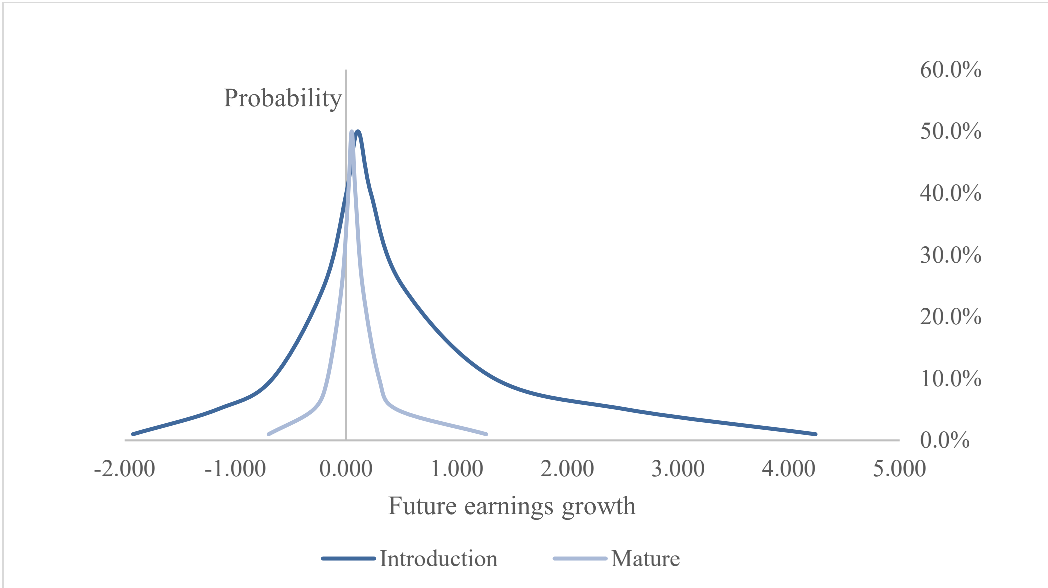
Analysts' forecast errors over the 12 months following the current year's earnings announcement



The graph plots mean signed analysts' forecast errors for introduction firms, mature firms, and the full sample. Forecast errors are shown for 11 months following the current year's earnings announcement and leading up to the next year's earnings announcement. The time period runs from 1989 to 2018, with analysts' forecast errors being tracked up to December 2019. All variables are defined in the Appendix.

FIGURE 5

Probability distribution of future earnings growth



The figure illustrates the probability distribution function of future earnings growth (EGR_{t+1}) for introduction and mature companies. It is based on 11 quantile estimates derived from quantile regressions of EGR_{t+1} on firm life cycle indicators of year *t* (introduction, growth, mature, shake-out and decline) in the set $\tau \in \{0.01, 0.05, 0.10, 0.25, 0.40, 0.50, 0.60, 0.75, 0.90, 0.95, 0.99\}$. The time period *t* runs from 1989 to 2018. All variables are defined in the Appendix.

TABLE 1

Cash flow patterns and firm life cycle

	Introduction	Growth	Mature	Shake-Out	Shake-Out	Shake-Out	Decline	Decline
CFO	-	+	+	-	+	+	-	-
CFI	-	-	-	-	+	+	+	+
CFF	+	+	-	-	+	-	+	-

The table reports eight cash flow pattern combinations that are collapsed into five life cycle stages: Introduction, Growth, Mature, Shake-Out and Decline. The cash flow patterns are based on the signs of net operating cash flow (*CFO*), net investing cash flow (*CFI*), and net financing cash flow (*CFF*) (Dickinson, 2011).

TABLE 2

Sample formation

Panel A: Data selection

	Firm-years	Firms
Matched Compustat/CRSP for the period 1989-2018	189,683	20,805
Less stocks other than NYSE, AMEX or NASDAQ stocks	-14,055	-1,833
Sample with stocks listed on NYSE, AMEX or NASDAQ	175,628	18,972
Less stocks other than ordinary common stocks	-27,674	-2,888
Sample with ordinary common stocks listed on NYSE, AMEX, NASDAQ	147,954	16,084
Less financial firms	-28,944	-2,898
Non-financials with ordinary common stocks listed on NYSE, AMEX or Nasdaq	119,010	13,186
Less observations with missing *firm life cycle*	-1,660	-103
Sample with non-missing required information	117,350	13,083
Require $ME_t \geq \$10m$	-10,301	-957
Final sample for the period 1989-2018	107,049	12,126

Panel B: Life cycle stage composition

Life cycle stage	N	%
Introduction	18,447	17.23
Growth	32,412	30.28
Mature	40,011	37.38
Shake-Out	8,706	8.13
Decline	7,473	6.98
Total	107,049	100

Panel C: Mean firm characteristics by life cycle stage

Life cycle stage	Age	ME	BM	R&D	OP	AGR	ACC
Introduction	8.086	386	0.524	0.320	-0.271	0.857	0.006
Growth	14.529	2504	0.580	0.081	0.154	0.460	-0.033
Mature	21.260	5101	0.618	0.065	0.149	0.046	-0.051
Shake-Out	17.743	2773	0.728	0.153	0.059	0.001	-0.050
Decline	10.680	385	0.604	0.559	-0.203	0.006	-0.034

Panel A reports the sample formation for the period 1989–2018, Panel B reports the life cycle stage composition of the sample, and Panel C reports mean firm characteristics for each firm life cycle stage. Firm life cycle is measured based on cash flow patterns, as shown in Table 1. All variables are defined in the Appendix.

TABLE 3

Hedge portfolio strategies

Panel A: Raw returns

	Return-weighted			Value-weighted		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	-0.030	-0.060	(0.952)	0.278	0.612	(0.541)
Growth	0.926	2.809	(0.005)	0.888	3.273	(0.001)
Mature	1.262	4.634	(0.000)	0.997	5.115	(0.000)
Shake-Out	1.243	3.631	(0.000)	0.823	3.218	(0.001)
Decline	0.727	1.371	(0.171)	1.013	2.273	(0.024)
Mature - Introduction	1.291	4.167	(0.000)	0.719	2.116	(0.035)

Panel B: FF3 adjusted returns

	Return-weighted			Value-weighted		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	-0.969	-4.741	(0.000)	-0.668	-4.035	(0.000)
Growth	0.068	0.761	(0.447)	0.161	2.631	(0.009)
Mature	0.505	6.934	(0.000)	0.408	7.329	(0.000)
Shake-Out	0.415	4.113	(0.000)	0.123	1.202	(0.230)
Decline	-0.214	-0.829	(0.407)	0.067	0.348	(0.728)
Mature - Introduction	1.473	7.265	(0.000)	1.076	5.780	(0.000)

The table presents average monthly stock returns (in percent) of five portfolios formed on the basis of firm life cycle. Following Asparouhova et al. (2013), I use two portfolio weighting schemes; prior period gross return-weighting (RW) and value-weighting (VW). Long/short positions are taken in each month on mature/introduction firms, allowing for a three-month lag between fiscal year-end and portfolio formation date. Panel A reports raw portfolio returns and Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors (FF3). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix.

TABLE 4

Firm-level monthly regressions

	1	2	3
Introduction	-0.030	0.517	0.513
	(0.952)	(0.176)	(0.178)
Growth	0.926	0.976	0.987
	(0.005)	(0.006)	(0.005)
Mature	1.262	1.157	1.184
	(0.000)	(0.001)	(0.000)
Shake-Out	1.243	1.244	1.218
	(0.000)	(0.000)	(0.001)
Decline	0.727	1.055	0.830
	(0.171)	(0.008)	(0.032)
Controls			
age		-0.043	-0.054
		(0.112)	(0.048)
logBP		0.098	0.201
		(0.075)	(0.000)
logME		-0.193	-0.159
		(0.002)	(0.010)
β		0.006	-0.034
		(0.952)	(0.732)
IdioRisk		-0.221	-0.255
		(0.084)	(0.040)
Illiquidity		-0.054	-0.028
		(0.275)	(0.546)
Ret^{-2-12}		0.311	0.304
		(0.000)	(0.000)
Ret^{-1}		-0.410	-0.423
		(0.000)	(0.000)
AGR		-0.124	-0.040
		(0.001)	(0.287)
OP		0.118	0.248
		(0.011)	(0.000)
ACC		-0.090	-0.093
		(0.005)	(0.003)
R&D			0.362
			(0.000)
Patent			0.071
			(0.020)
Citation			0.067
			(0.003)
Mature - Introduction	1.291	0.641	0.671
	(0.000)	(0.000)	(0.000)
Adj. R2	0.099	0.143	0.146

The table reports results from Fama-MacBeth regressions of future monthly firm-level stock returns (in percent) on firm life cycle stage indicators and control variables. Firm life cycle indicators are obtained monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Introduction, Growth, Mature, Shake-out and Decline are (0, 1) dummies that take the value of one if the firm belongs to the corresponding life cycle stage and zero otherwise. The control variables include age (*age*), log book-to-market (*logBP*), log market capitalization (*logME*), market beta (β), idiosyncratic volatility (*IdioRisk*), illiquidity (*Illiquidity*), momentum ($Ret^{-2\text{-}12}$), reversal (Ret^{-1}), asset growth (*AGR*), operating profitability (*OP*), accruals (*ACC*), R&D intensity (*R&D*), patent intensity (*Patent*) and patent citation impact (*Citation*). Following Asparouhova et al. (2010), regressions are weighted by prior period gross returns (RW). The sample is based on 1,226,788 monthly observations covering the period 199004–201912. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. Reported R2s are time-series means of monthly adjusted R2s. All variables are defined in the Appendix.

TABLE 5

Returns on earnings announcement days

Panel A: Market-adjusted returns around earnings announcement dates

	Window (-1, +1)			Window (-3, +3)			Window (-5, +5)		
	Mean	*t*-test	*p*-value	Mean	*t*-test	*p*-value	Mean	*t*-test	*p*-value
Introduction	-0.023	-5.989	(0.000)	-0.031	-4.936	(0.000)	-0.032	-3.904	(0.001)
Growth	0.009	3.666	(0.001)	0.010	2.212	(0.035)	0.013	2.038	(0.051)
Mature	0.013	4.161	(0.000)	0.017	3.682	(0.001)	0.021	3.373	(0.002)
Shake-Out	0.011	3.450	(0.002)	0.014	2.445	(0.021)	0.016	2.055	(0.049)
Decline	-0.016	-3.444	(0.002)	-0.014	-1.936	(0.063)	-0.012	-1.163	(0.255)
Mature - Introduction	0.036	8.414	(0.000)	0.048	6.919	(0.000)	0.053	6.231	(0.000)

TABLE 5 (Continued)

Panel B: Returns on earnings announcement days versus non-earnings announcement days

	Window (-1, +1)		Window (-3, +3)		Window (-5, +5)	
	1	2	3	4	5	6
Intercept		0.062		0.062		0.060
		(0.000)		(0.000)		(0.000)
Introduction	0.039	-0.018	0.040	-0.018	0.041	-0.016
	(0.003)	(0.011)	(0.002)	(0.016)	(0.002)	(0.034)
Growth	0.062	0.005	0.060	0.002	0.058	0.001
	(0.000)	(0.515)	(0.000)	(0.791)	(0.000)	(0.913)
Mature	0.084	0.020	0.084	0.019	0.083	0.019
	(0.000)	(0.004)	(0.000)	(0.010)	(0.000)	(0.012)
Shake-Out	0.076	0.015	0.077	0.015	0.077	0.016
	(0.000)	(0.035)	(0.000)	(0.052)	(0.000)	(0.044)
Decline	0.054	-	0.055	-	0.054	-
	(0.000)	-	(0.000)	-	(0.000)	-
Introduction × *Eday*	-0.179	-0.161	-0.093	-0.073	-0.061	-0.044
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.001)
Growth × *Eday*	0.103	0.107	0.061	0.071	0.055	0.064
	(0.000)	(0.000)	(0.002)	(0.000)	(0.003)	(0.000)
Mature × *Eday*	0.096	0.115	0.048	0.067	0.036	0.054
	(0.000)	(0.000)	(0.001)	(0.000)	(0.010)	(0.000)
Shake-Out × *Eday*	0.083	0.095	0.027	0.049	0.016	0.037
	(0.005)	(0.000)	(0.204)	(0.001)	(0.403)	(0.001)
Decline × *Eday*	-0.156	-0.131	-0.081	-0.057	-0.042	-0.024
	(0.000)	(0.001)	(0.007)	(0.021)	(0.101)	(0.224)
Intercept + Introduction	-0.140	-0.117	-0.053	-0.029	-0.020	0.000
+ Introduction × *Eday*	(0.000)	(0.000)	(0.044)	(0.079)	(0.375)	(0.945)
Intercept + Mature +	0.180	0.197	0.132	0.148	0.119	0.133
Mature × Eday	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R2	0.010	0.072	0.010	0.072	0.010	0.072
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm-day	Firm-day	Firm-day	Firm-day	Firm-day	Firm-day
Fixed Effects	No	Day	No	Day	No	Day

Panel A presents mean excess earnings announcement returns across portfolios formed on the basis of firm life cycle. For each firm in a portfolio, I calculate excess buy-and-hold returns in the [-1, +1], [-3, +3] and [-5, +5] event windows centered on the quarterly earnings announcement date. I then aggregate these returns over the four quarters following fiscal year-end. Excess returns are measured as buy-and-hold raw returns minus the buy-and-hold return on the value-weighted market portfolio. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. The sample period runs from 1989 to 2017, so that earnings announcement returns over the *four* subsequent quarters are available in each year. Panel B reports results from regressing daily returns (in percent) on firm life cycle stage indicators, interactions between firm life cycle indicators and earnings day indicators (*Eday*), and control variables (coefficients unreported). Following Asparouhova et al. (2010), regressions are weighted by prior period gross returns (RW). Introduction, Growth, Mature, Shake-out, Decline are (0, 1) dummies equal to one when a firm-day belongs to the corresponding life cycle stage and zero otherwise. *Eday* is a (0,1) dummy variable equal to one over the three-day, seven-day or eleven-day window around an earnings announcement date. The control variables include age, log book-to-market, log market capitalization, market beta, idiosyncratic volatility, illiquidity, momentum, reversal, asset growth, operating profitability, accruals, R&D intensity, patent intensity, patent citation impact, 10 lagged values of the daily return, 10 lagged values of the daily squared return and 10 lagged values of the daily trading volume. The sample is based on 25,696,595 daily observations covering the period 199004–201912. Standard errors are clustered by firm and day. All variables are defined in the Appendix.

TABLE 6

Analysts' forecast errors

Panel A: Analyst' forecast errors as of three months after fiscal year-end

	Mean	*t*-stat	*p*-value
Introduction	-0.039	-8.523	(0.000)
Growth	-0.013	-6.347	(0.000)
Mature	-0.008	-5.387	(0.000)
Shake-Out	-0.015	-5.150	(0.000)
Decline	-0.027	-3.398	(0.002)
Mature - Introduction	0.031	8.562	(0.000)

Panel B: Analysts' forecast errors over time

Month	*All Observations*	Introduction	Mature	Mature - Introduction	*t*-stat	*p*-value
1	-0.017	-0.044	-0.008	0.036	6.865	(0.000)
2	-0.015	-0.041	-0.008	0.033	6.247	(0.000)
3	-0.014	-0.036	-0.007	0.029	5.305	(0.000)
4	-0.013	-0.034	-0.007	0.027	5.415	(0.000)
5	-0.012	-0.030	-0.006	0.024	5.241	(0.000)
6	-0.010	-0.026	-0.005	0.021	5.154	(0.000)
7	-0.009	-0.024	-0.004	0.019	5.269	(0.000)
8	-0.007	-0.021	-0.003	0.018	6.063	(0.000)
9	-0.006	-0.017	-0.002	0.015	6.296	(0.000)
10	-0.005	-0.016	-0.002	0.015	6.571	(0.000)
11	-0.004	-0.015	-0.001	0.014	5.788	(0.000)

The table reports mean signed analysts' forecast errors for five portfolios formed on the basis of firm life cycle. In Panel A, analysts' forecasts are obtained three months after fiscal year-end. In Panel B, analysts' forecast errors are tracked over the 11 months following the current year's earnings announcement and leading up to the next year's earnings announcement. The time period runs from 1989 to 2018, with analysts' forecast errors being tracked up to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix.

TABLE 7

Earnings growth and uncertainty in earnings growth

	5%	10%	25%	40%	50%	60%	75%	90%	95%	OLS	IQR	SKEW
Introduction	-1.164	-0.663	-0.199	0.002	0.106	0.224	0.509	1.341	2.536	0.276	2.004	0.232
	(0.000)	(0.000)	(0.000)	0.807	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Growth	-0.379	-0.189	-0.011	0.072	0.122	0.179	0.298	0.599	0.937	0.190	0.788	0.211
	(0.000)	(0.000)	(0.343)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Mature	-0.293	-0.168	-0.039	0.020	0.051	0.084	0.149	0.299	0.459	0.074	0.466	0.063
	(0.000)	(0.000)	(0.000)	0.017	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Shake-Out	-0.540	-0.314	-0.105	-0.008	0.041	0.090	0.203	0.529	0.960	0.115	0.843	0.158
	(0.000)	(0.000)	(0.000)	0.318	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Decline	-1.081	-0.617	-0.208	-0.033	0.066	0.176	0.421	1.209	2.280	0.228	1.826	0.251
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Mature - Introduction	0.871	0.496	0.160	0.018	-0.055	-0.140	-0.361	-1.042	-2.077	-0.202	-1.538	0.169
p-value	(0.000)	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
R^2	0.106	0.063	0.019	0.007	0.008	0.015	0.037	0.092	0.144	0.014	NA	

The table reports results from Fama-MacBeth quantile and OLS regressions of earnings growth in year $t+1$ (EGR_{t+1}) on firm life cycle stage indicators in year t. Introduction, Growth, Mature, Shake-out, Decline are (0, 1) dummies that take the value of one when a firm-year belongs to the corresponding life cycle stage and zero otherwise. Quantile regressions are estimated for quantiles in the set $\tau \in \{0.05, 0.10, 0.25, 0.40, 0.50, 0.60, 0.75, 0.90, 0.95\}$. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. Reported R2s are time-series means of annual pseudo (adjusted) R2s for quantile (OLS) regressions. Q_τ denotes the estimated τ'th quantile of EGR_{t+1} conditional on firm life cycle. *IQR* is a measure of uncertainty in EGR_{t+1}, defined as $Q_{90} - Q_{10}$. *SKEW* is a measure of skewness in EGR_{t+1}, defined as $(Q_{90} - Q_{10} - 2\times Q_{50})/IQR$. The sample is based on 107,049 firm-year observations covering the period 1989–2018. All variables are defined in the Appendix.

TABLE 8

Association with sentiment

Panel A: Raw returns

	Low sentiment	Medium Sentiment	High sentiment	High-Low	*t*-stat	*p*-value
Introduction	1.332	0.109	-1.723	-3.056	-2.371	(0.018)
t-stat	1.420	0.163	-1.943			
p-value	(0.157)	(0.871)	(0.053)			
Mature	1.470	1.123	1.134	-0.335	-0.461	(0.645)
t-stat	2.382	2.886	2.924			
p-value	(0.018)	(0.004)	(0.004)			
Mature-Introduction	0.137	1.013	2.858	2.721	3.471	(0.001)
t-stat	0.283	2.500	4.637			
p-value	(0.778)	(0.013)	(0.000)			
N	115	115	115			

Panel B: FF3 adjusted returns

	Low sentiment	Medium Sentiment	High sentiment	MKT–RF	SMB	HML	High–Low
Introduction	-0.248	-1.087	-1.621	1.232	1.290	-0.250	-1.373
t-stat	-0.613	-3.406	-4.294	19.139	13.476	-2.050	-2.432
p-value	(0.540)	(0.001)	(0.000)	(0.000)	(0.000)	(0.041)	(0.016)
Mature	0.470	0.390	0.681	0.930	0.574	0.386	0.210
t-stat	3.415	3.981	4.645	33.163	9.731	8.359	1.019
p-value	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.309)
Mature-Introduction	0.718	1.477	2.302	-0.302	-0.716	0.636	1.583
t-stat	1.905	4.821	6.558	-5.224	-8.084	6.116	3.043
p-value	(0.058)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)

The table reports average monthly stock returns (in percent) of a hedge portfolio strategy formed on the basis of firm life cycle conditional on investor sentiment. Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Investor sentiment is the orthogonalized sentiment index from Baker and Wurgler (2006). It is measured in the month preceding the return calculation and is classified into three equal-sized groups: high, medium and low. Panel A reports raw portfolio returns and Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors (FF3). Portfolio returns are prior period gross return-weighted (RW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix.

TABLE 9

Limits to arbitrage proxied by residual institutional ownership

Panel A: Raw returns

	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.422	0.602	0.730	1.152	(0.000)
Growth	0.790	1.058	1.001	0.212	(0.040)
Mature	1.149	1.315	1.304	0.154	(0.128)
Shake-Out	0.991	1.293	1.427	0.437	(0.010)
Decline	0.232	1.175	1.160	0.929	(0.000)
Mature - Introduction	1.572	0.713	0.574	-0.998	(0.000)
p-value	(0.000)	(0.018)	(0.029)		

Panel B: FF3 adjusted returns

	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Introduction	-1.378	-0.335	-0.213	1.165	(0.000)
Growth	-0.025	0.189	0.106	0.131	(0.182)
Mature	0.460	0.565	0.481	0.021	(0.790)
Shake-Out	0.190	0.465	0.578	0.387	(0.020)
Decline	-0.702	0.219	0.213	0.915	(0.000)
Mature - Introduction	1.838	0.900	0.694	-1.145	(0.000)
p-value	(0.000)	(0.000)	(0.001)		

The table presents average monthly stock returns (in percent) of portfolios sorted independently on firm life cycle and residual institutional ownership (RI). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Residual institutional ownership is obtained at least one quarter prior fiscal year-end and is orthogonalized with respect to size and size-squared (Nagel, 2005). Panel A reports raw portfolio returns and Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors (FF3). Portfolio returns are prior period gross return-weighted (RW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix.

TABLE 10

Limits to arbitrage proxied by idiosyncratic volatility

Panel A: Raw returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	0.279	0.297	-0.155	-0.434	(0.289)
Growth	0.985	0.989	0.710	-0.275	(0.398)
Mature	1.131	1.336	1.402	0.271	(0.339)
Shake-Out	1.138	1.178	1.293	0.155	(0.654)
Decline	0.388	0.989	0.670	0.282	(0.542)
Mature - Introduction	0.851	1.039	1.557	0.706	(0.009)
p-value	(0.000)	(0.000)	(0.000)		

Panel B: FF3 adjusted returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.396	-0.568	-1.138	-0.742	(0.010)
Growth	0.314	0.087	-0.341	-0.655	(0.001)
Mature	0.481	0.514	0.465	-0.016	(0.931)
Shake-Out	0.474	0.341	0.333	-0.140	(0.556)
Decline	-0.291	0.149	-0.323	-0.032	(0.928)
Mature - Introduction	0.877	1.083	1.603	0.726	(0.002)
p-value	(0.000)	(0.000)	(0.000)		

The table presents average monthly stock returns (in percent) of portfolios sorted independently on firm life cycle and idiosyncratic return volatility (IdioRisk). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Idiosyncratic volatility is calculated as the standard deviation of residuals obtained from a regression of daily stock returns on the CRSP value-weighted market return over the 12 months ending three months after fiscal year-end. Panel A reports raw portfolio returns and Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors (FF3). Portfolio returns are prior period gross return-weighted (RW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix.

Firm Life Cycle, Expectation Errors and Future Stock Returns

Online Appendix

Robustness section

This online appendix provides supplementary material for the article "Firm life cycle, expectation errors and future stock returns". In particular, this document includes:

- details of various robustness tests (Sections 1–5).
- additional results (Figure OA-1 and Tables OA-1 to OA-20).

1. Value-weighted portfolios

In the main results of the paper, I use primarily prior-period gross (one-plus) return weights (RW) to correct for the bias associated with microstructure noise in stock returns (bid-ask bounce, non-synchronous trading, temporary effects of order imbalances, etc.) (see Asparouhova et al., 2010, 2013).[24] To provide a complete analysis, I report results using value-weights (VW) in this online appendix. All of my inferences remain unaltered (Tables OA-1, OA-4, OA-6 and OA-8).

2. Risk-adjusted returns

Throughout the paper, I use the three factor Fama and French (1993) model to compute abnormal returns ("alphas"). This is in line with Dickinson (2011), who computes size- and book-to-market-adjusted returns for the five firm life cycle portfolios.[25] For robustness, I repeat all of my tests using the five factor Fama and French (2015) model and the Hou et al. (2015) *q*-factor model. I continue to find that mature firms outperform introduction firms, and that this effect is stronger among stocks with low institutional ownership and following periods of high sentiment – these results hold using both RW and VW portfolio returns (Table OA-2 and Tables OA-3 to OA-6). Results using double sorts with idiosyncratic volatility are less robust; when using the five factor Fama and French (2015) model, the firm life cycle effect continues to increase with higher idiosyncratic volatility, but only for RW portfolios. When using the *q*-factor model, idiosyncratic

[24]Asparouhova et al., (2013, p.667) write: "In terms of effectiveness in mitigating biases in portfolio mean return estimates, the analysis provides little reason to prefer VW over RW, or vice versa. Although each is effective in mitigating bias, the former places greater weight on large firms whereas the latter places essentially equal weight on each security in the sample. The final choice may therefore depend on researchers' preferences for weighting the information contained in the small versus large firms in the sample".

[25] A large amount of research shows evidence that size and book-to-market relate to systematic risk (e.g. Campbell and Vuolteenaho, 2004), whereas evidence linking systematic risk to the profitability and investment factors of the five-factor Fama and French (2015) model is sparse.

volatility has no impact on the firm life cycle strategy, regardless of the weighting scheme (Tables OA-7 to OA-8). The latter result underlines the significance of understanding the driving forces behind the investment and profitability factors (see Hou et al., 2015 for a related discussion).

3. Measuring excess earnings announcement returns

In the earnings announcement tests of the paper (Panel A of Table 5), I calculate earnings announcement returns *in excess of* the value-weighted market return, consistent with prior literature (La Porta, 1996; Bernard et al., 1997). Results are robust when I use the market model or the Fama and French (1993) three factor model to compute excess earnings announcement returns. Introduction firms continue to earn negative excess returns around subsequent earnings announcement days, and mature firms continue to earn positive excess returns (see Table OA-9).

4. Dynamic risk exposures in earnings announcement days

Further earnings announcement tests in the paper (Panel B of Table 5) indicate that introduction firms earn lower returns and mature firms earn higher returns on information days compared to non-information days. While this evidence is at odds with a static risk factor model, whereby betas are time-invariant, it is consistent with a dynamic risk model, whereby risk exposures change on information days (Engelberg et al., 2018). Specifically, if risk exposures increase (decrease) for mature (introduction) firms when earnings is released, then this could result in higher (lower) returns for mature (introduction) firms.[26]

To control for this possibility, I estimate the following regression model, which allows market betas to change on information days:

[26] Patton and Verardo (2012) show evidence that a stock's market beta increases on earnings announcement days, which could provide a risk-based explanation for why mature firms earn higher returns when they disclose their earnings.

$$R_{it} = \sum_{j=1}^{5} a_j Firm\ Life\ Cycle_{it}^{j} + \sum_{j=1}^{5} \beta_j Firm\ Life\ Cycle_{it}^{j} \times Eday_{i,t}$$

$$+ \sum_{j=1}^{5} \gamma_j Firm\ Life\ Cycle_{it}^{j} \times Market_t + \sum_{j=1}^{5} \delta_j Firm\ Life\ Cycle_{it}^{j} \times Eday_{i,t} \times Market_t$$

$$+ \sum_{k} \gamma_\kappa\, Control_{it}^{k} + \varepsilon_{it} \qquad (OA.1)$$

R_{it} is the daily return of stock i on day t. $Firm\ Life\ Cycle_{it}^{j}$ is a dummy variable taking the value of one if firm i belongs to a certain life cycle stage on day t, and zero otherwise – it is denoted as *Introduction*, *Growth*, *Mature*, *Shake-Out* and *Decline* for j = 1, 2, 3, 4 and 5 respectively. $Eday_{it}$ is a dummy variable equal to one on earnings announcement days for firm i and zero otherwise. $Market_t$ is the daily value-weighted market index. Firm life cycle is defined at the beginning of each month and remains the same throughout the month. Interaction terms indicate whether portfolio returns are higher on earnings announcement days. The control variables include 10 lagged values of the daily return, 10 lagged values of the daily squared return, 10 lagged values of the daily trading volume and all of the controls of Table 4 (unreported for brevity). Day fixed effects are included and standard errors are clustered by firm and day. The results are reported in Table OA-10. All inferences remain.

5. Subsample analysis

In this section, I perform a subsample analysis, using July 2011 (i.e. the Dickinson (2011) publication date) as a cut-off point, to investigate whether the firm life cycle effect in stock returns is still present in the recent years.[27] [28] The results show that mature firms continue to outperform introduction firms in the post-publication period. However, this result is only significant when using RW portfolios – not when using VW portfolios (Tables OA-11 to OA-13 of this online appendix). In addition, the life cycle hedge portfolio return continues to be more pronounced among stocks with low institutional ownership, but not among stocks with high idiosyncratic volatility (Tables OA-14 to OA-17).

[27] I thank the Referee for this suggestion.
[28] The post-publication period starts August 2011 and returns are being tracked from September 2011 onwards. In tests that utilize annual data, I split the sample into the periods 1987–2010 and 2011–2018.

Results from quantile regressions show that, in the post-publication period, introduction firms continue to have greater uncertainty and skewness in future earnings growth than mature firms, however the magnitude of earnings skewness for introduction firms is somewhat smaller (0.143 vs. 0.264) (Table OA-18). To the extent that earnings skewness promotes analysts' forecast optimism (see discussion on page 14 of the paper), a reduction in earnings skewness may lead to lower analysts' forecast bias in the post-publication period. Additional tests show that this is indeed the case. Although analysts' forecast errors continue to be negative for introduction firms in both subsamples (Tables OA-19 and OA-20), they decrease by half in the post-publication period (–0.023 vs. –0.045).

Overall, the results in this section suggest that the firm life cycle effect in stock returns is decreasing over time. Analysts' forecast errors with respect to firm life cycle are going down, and so do the predictable future stock returns. While a number of factors may be contributing to this trend (e.g. increase in arbitrage capital, change in the earnings properties (e.g. skewness) of introduction/mature firms), a likely cause is the decreasing pattern in the level of investor sentiment over time (shown in Figure OA-1 of the online appendix). Specifically, the mean level of investor sentiment is equal to 0.296 and -0.044 in the pre- and post- publication periods respectively, consistent with evidence in the paper that the firm life cycle return predictability is stronger following periods of high sentiment.

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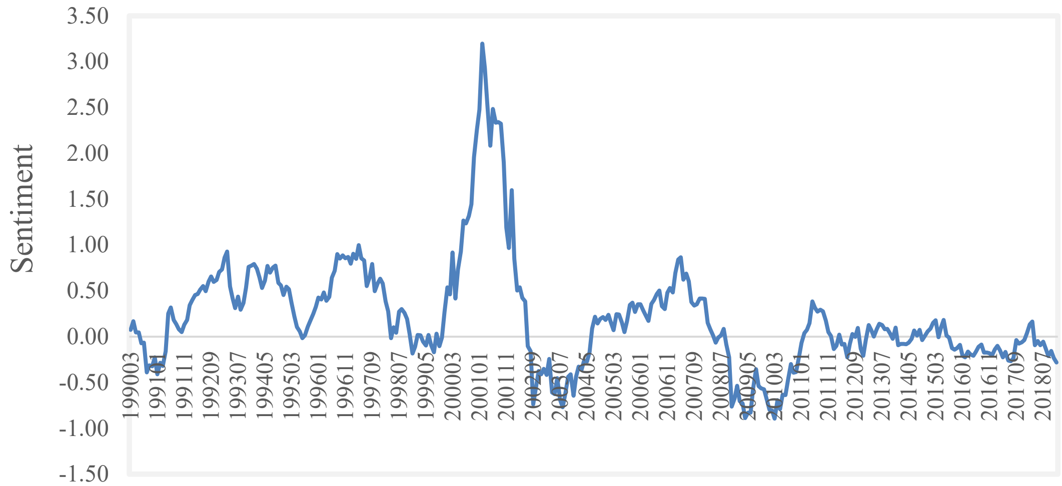
Figure OA-1: Market sentiment over time



This figure plots the orthogonalized sentiment index of Baker and Wurgler (2006) over time, from March 1990 to December 2018.

TABLE OA-1

Fama-MacBeth regressions of firm-level returns on firm life cycle and controls (VW)

	1	2	3
Introduction	0.278	0.545	0.546
	(0.541)	(0.158)	(0.154)
Growth	0.888	0.954	1.020
	(0.001)	(0.010)	(0.006)
Mature	0.997	1.001	1.069
	(0.000)	(0.005)	(0.003)
Shake-Out	0.823	0.881	0.944
	(0.001)	(0.017)	(0.011)
Decline	1.013	1.102	1.020
	(0.024)	(0.008)	(0.013)
Controls			
age		-0.050	-0.050
		(0.095)	(0.102)
logBP		-0.017	0.002
		(0.799)	(0.974)
logME		-0.109	-0.155
		(0.165)	(0.046)
β		0.063	0.013
		(0.645)	(0.921)
IdioRisk		-0.213	-0.296
		(0.169)	(0.046)
Illiquidity		0.036	0.035
		(0.679)	(0.678)
Ret^{-2-12}		0.253	0.241
		(0.013)	(0.016)
Ret^{-1}		-0.299	-0.304
		(0.002)	(0.001)
AGR		-0.109	-0.086
		(0.030)	(0.074)
OP		0.154	0.143
		(0.054)	(0.057)
ACC		-0.119	-0.099
		(0.034)	(0.063)
R&D			0.290
			(0.003)
Patent			-0.005
			(0.934)
Citation			0.076
			(0.038)
Mature - Introduction	0.719	0.456	0.524
	(0.035)	(0.021)	(0.007)
Adj. R2	0.177	0.298	0.313

The table reports results from Fama-MacBeth regressions of future monthly firm-level stock returns (in percent) on firm life cycle stage indicators and control variables. Firm life cycle indicators are obtained monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Introduction, Growth, Mature, Shake-out and Decline are (0, 1) dummies that take the value of one if the firm belongs to the corresponding life cycle stage and zero otherwise. The control variables include age (*age*), log book-to-market (*logBP*), log market capitalization (*logME*), market beta (β), idiosyncratic volatility (*IdioRisk*), illiquidity (*Illiquidity*), momentum (Ret^{-2-12}), reversal (Ret^{-1}), asset growth (*AGR*), operating profitability (*OP*), accruals (*ACC*), R&D intensity (*R&D*), patent intensity (*Patent*) and patent citation impact (*Citation*). Regressions are value-weighted (VW). The sample is based on 1,226,788 monthly observations covering the period 199004–201912. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. Reported R2s are time-series means of monthly adjusted R2s. All variables are defined in the Appendix of the paper.

TABLE OA-2

Hedge portfolio strategies

Panel A: FF5 adjusted returns

	Return-weighted			Value-weighted		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	-0.488	-2.355	(0.019)	-0.270	-1.696	(0.091)
Growth	0.099	1.040	(0.299)	0.255	4.201	(0.000)
Mature	0.383	5.339	(0.000)	0.253	5.867	(0.000)
Shake-Out	0.474	4.183	(0.000)	0.040	0.383	(0.702)
Decline	0.229	0.939	(0.348)	0.296	1.706	(0.089)
Mature - Introduction	0.872	5.003	(0.000)	0.524	3.094	(0.002)

Panel B: *Q*-factor adjusted returns

	Return-weighted			Value-weighted		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	-0.186	-0.791	(0.429)	-0.200	-0.945	(0.345)
Growth	0.272	2.450	(0.015)	0.282	4.396	(0.000)
Mature	0.506	4.690	(0.000)	0.310	6.001	(0.000)
Shake-Out	0.663	5.311	(0.000)	0.066	0.577	(0.564)
Decline	0.592	2.059	(0.040)	0.497	2.269	(0.024)
Mature - Introduction	0.692	3.077	(0.002)	0.511	2.225	(0.027)

The table presents average monthly stock returns (in percent) of five portfolios formed on the basis of firm life cycle. Following Asparouhova et al. (2013), I use two portfolio weighting schemes; prior period gross return-weighting (RW) and value-weighting (VW). Long/short positions are taken in each month on mature/introduction firms, allowing for a three-month lag between fiscal year-end and portfolio formation date. Panel A presents intercepts from regressions of portfolio returns on the five Fama and French (2015) factors (FF5) and Panel B presents intercepts from regressions of portfolio returns on the Hou et al. (2015) *q*-factors. The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-3

Association with Sentiment (RW)

Panel A: FF5 adjusted returns

	Low Sentiment	Medium Sentiment	High Sentiment	MKT–RF	SMB	HML	RMW	CMA	High-Low
Introduction	0.171	-0.865	-0.803	1.034	0.976	-0.177	-0.973	-0.175	-0.975
t-stat	0.479	-3.051	-1.998	16.141	10.247	-1.261	-7.697	-0.857	-1.915
p-value	(0.632)	(0.002)	(0.047)	(0.000)	(0.000)	(0.208)	(0.000)	(0.392)	(0.056)
Mature	0.373	0.307	0.518	0.974	0.659	0.191	0.199	0.097	0.144
t-stat	2.929	3.288	3.681	33.787	17.056	3.734	4.103	1.419	0.771
p-value	(0.004)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.157)	(0.441)
Mature-Introduction	0.202	1.172	1.321	-0.060	-0.317	0.368	1.172	0.272	1.119
t-stat	0.675	4.597	4.289	-1.225	-4.443	3.481	11.819	1.749	2.766
p-value	(0.500)	(0.000)	(0.000)	(0.221)	(0.000)	(0.001)	(0.000)	(0.081)	(0.006)

Panel B: *Q*-factor adjusted returns

	Low Sentiment	Medium Sentiment	High Sentiment	MKT–RF	ME	IA	ROE	High-Low
Introduction	0.080	-0.140	-0.630	0.937	0.942	-0.562	-1.147	-0.710
t-stat	0.228	-0.407	-1.517	14.105	11.726	-3.507	-7.873	-1.377
p-value	(0.820)	(0.685)	(0.130)	(0.000)	(0.000)	(0.001)	(0.000)	(0.169)
Mature	0.441	0.343	0.811	0.911	0.527	0.316	-0.137	0.370
t-stat	3.272	2.915	3.985	24.134	7.057	4.058	-1.801	1.648
p-value	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.073)	(0.100)
Mature-Introduction	0.361	0.483	1.441	-0.026	-0.415	0.878	1.010	1.080
t-stat	1.001	1.419	4.215	-0.434	-4.970	6.261	7.176	2.304
p-value	(0.318)	(0.157)	(0.000)	(0.665)	(0.000)	(0.000)	(0.000)	(0.022)

The table reports average monthly stock returns (in percent) of a hedge portfolio strategy formed on the basis of firm life cycle conditional on investor sentiment. Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Investor sentiment is the orthogonalized sentiment index from Baker and Wurgler (2006). It is measured in the month preceding the return calculation and is classified into three equal-sized groups: high, medium and low. Panel A presents intercepts from regressions of portfolio returns on the five Fama and French (2015) factors (FF5) and Panel B presents intercepts from regressions of portfolio returns on the Hou et al. (2015) *q*-factors. Portfolio returns are prior period gross return-weighted (RW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-4

Association with Sentiment (VW)

Panel A: Raw returns

	Low sentiment	Medium Sentiment	High Sentiment	High-Low	*t*-stat	*p*-value
Introduction	1.451	0.948	-1.750	-3.201	-2.783	(0.006)
t-stat	1.792	1.433	-2.141			
p-value	(0.074)	(0.153)	(0.033)			
Mature	1.042	1.030	0.801	-0.241	-0.474	(0.636)
t-stat	2.547	3.420	2.630			
p-value	(0.011)	(0.001)	(0.009)			
Mature-Introduction	-0.408	0.082	2.551	2.959	3.524	(0.000)
t-stat	-0.780	0.166	3.886			
p-value	(0.436)	(0.868)	(0.000)			
N	115	115	115			

Panel B: FF3 adjusted returns

	Low sentiment	Medium Sentiment	High Sentiment	MKT–RF	SMB	HML	High-Low
Introduction	-0.160	-0.386	-1.445	1.370	0.853	-0.529	-1.284
t-stat	-0.534	-1.407	-6.358	30.171	14.421	-8.172	-3.458
p-value	(0.594)	(0.160)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Mature	0.270	0.328	0.652	0.869	-0.133	0.011	0.382
t-stat	3.646	4.261	6.231	56.369	-6.971	0.348	3.147
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.728)	(0.002)
Mature-Introduction	0.430	0.714	2.096	-0.502	-0.986	0.539	1.666
t-stat	1.322	2.315	8.241	-9.868	-16.230	6.833	4.102
p-value	(0.187)	(0.021)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

TABLE OA-4 (Continued)

Panel C: FF5 adjusted returns

	Low Sentiment	Medium Sentiment	High Sentiment	MKT–RF	SMB	HML	RMW	CMA	High-Low
Introduction	0.200	-0.196	-0.825	1.198	0.657	-0.370	-0.677	-0.357	-1.025
t-stat	0.765	-0.831	-3.548	25.338	10.743	-4.453	-6.700	-2.727	-3.031
p-value	(0.445)	(0.407)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.003)
Mature	0.121	0.246	0.430	0.939	-0.070	-0.114	0.217	0.228	0.308
t-stat	2.066	3.852	4.933	74.885	-3.361	-5.647	6.400	5.853	2.954
p-value	(0.040)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.003)
Mature-Introduction	-0.079	0.443	1.254	-0.260	-0.727	0.257	0.894	0.585	1.333
t-stat	-0.295	1.765	5.161	-5.404	-11.451	2.960	8.741	4.120	3.833
p-value	(0.768)	(0.079)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)

Panel D: *Q*-factor adjusted returns

	Low Sentiment	Medium Sentiment	High Sentiment	MKT–RF	ME	IA	ROE	High-Low
Introduction	0.150	0.221	-1.083	1.183	0.678	-0.892	-0.539	-1.233
t-stat	0.478	0.732	-3.638	22.356	10.908	-7.018	-5.046	-3.069
p-value	(0.633)	(0.465)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Mature	0.222	0.231	0.521	0.908	-0.108	0.112	0.099	0.298
t-stat	3.244	3.004	5.247	61.964	-5.753	2.919	2.944	2.587
p-value	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.004)	(0.003)	(0.010)
Mature-Introduction	0.072	0.010	1.604	-0.275	-0.786	1.005	0.638	1.531
t-stat	0.229	0.031	4.760	-4.778	-11.569	7.060	5.383	3.552
p-value	(0.819)	(0.976)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

The table reports average monthly stock returns (in percent) of a hedge portfolio strategy formed on the basis of firm life cycle conditional on investor sentiment. Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Investor sentiment is the orthogonalized sentiment index from Baker and Wurgler (2006). It is measured in the month preceding the return calculation and is classified into three equal-sized groups: high, medium and low. Panel A reports raw portfolio returns, Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors (FF3), Panel C presents intercepts from regressions of portfolio returns on the five Fama and French (2015) factors (FF5) and Panel D presents intercepts from regressions of portfolio returns on the Hou et al. (2015) *q*-factors. Portfolio returns are value-weighted (VW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-5

Limits to arbitrage proxied by residual institutional ownership (RW)

Panel A: FF5 adjusted returns

	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.749	0.028	-0.011	0.738	(0.000)
Growth	0.098	0.187	0.075	-0.024	(0.799)
Mature	0.420	0.412	0.335	-0.085	(0.304)
Shake-Out	0.333	0.514	0.573	0.240	(0.161)
Decline	-0.104	0.652	0.489	0.593	(0.019)
Mature - Introduction	1.169	0.384	0.346	-0.823	(0.000)
p-value	(0.000)	(0.049)	(0.065)		

Panel B: *Q*-factor adjusted returns

	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.490	0.305	0.433	0.922	(0.001)
Growth	0.282	0.362	0.250	-0.033	(0.741)
Mature	0.557	0.519	0.459	-0.099	(0.321)
Shake-Out	0.581	0.634	0.762	0.181	(0.330)
Decline	0.278	1.023	0.776	0.498	(0.066)
Mature - Introduction	1.047	0.214	0.026	-1.021	(0.000)
p-value	(0.000)	(0.343)	(0.905)		

The table presents average monthly stock returns (in percent) of portfolios sorted independently on firm life cycle and residual institutional ownership (RI). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Residual institutional ownership is obtained at least one quarter prior fiscal year-end and is orthogonalized with respect to size and size-squared (Nagel, 2005). Panel A presents intercepts from regressions of portfolio returns on the five Fama and French (2015) factors (FF5) and Panel B presents intercepts from regressions of portfolio returns on the Hou et al. (2015) *q*-factors. Portfolio returns are prior period gross return-weighted (RW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-6
Limits to arbitrage proxied by residual institutional ownership (VW)

Panel A: Raw returns

	Residual Institutional Ownership				
Small stocks	Low	Medium	High	High-Low	*p*-value
Introduction	-0.142	0.943	1.048	1.190	(0.000)
Growth	1.001	1.088	1.172	0.171	(0.294)
Mature	1.232	1.431	1.356	0.125	(0.416)
Shake-Out	0.962	1.359	1.721	0.759	(0.009)
Decline	0.202	1.358	0.992	0.790	(0.019)
Mature - Introduction	1.374	0.487	0.308	-1.066	(0.000)
p-value	(0.000)	(0.128)	(0.249)		
Big stocks	Low	Medium	High	High-Low	*p*-value
Introduction	0.194	0.500	0.271	0.076	(0.824)
Growth	0.758	1.017	0.969	0.212	(0.219)
Mature	1.029	0.911	1.218	0.189	(0.221)
Shake-Out	0.735	0.755	1.166	0.430	(0.086)
Decline	1.077	1.246	1.466	0.389	(0.352)
Mature - Introduction	0.835	0.411	0.947	0.113	(0.768)
p-value	(0.064)	(0.250)	(0.002)		

Panel B: FF3 adjusted returns

	Residual Institutional Ownership				
Small stocks	Low	Medium	High	High-Low	*p*-value
Introduction	-1.114	0.052	0.078	1.192	(0.000)
Growth	0.172	0.185	0.220	0.048	(0.749)
Mature	0.469	0.617	0.473	0.004	(0.974)
Shake-Out	0.171	0.556	0.786	0.615	(0.036)
Decline	-0.721	0.410	-0.004	0.717	(0.029)
Mature - Introduction	1.583	0.565	0.395	-1.188	(0.000)
p-value	(0.000)	(0.023)	(0.079)		
Big stocks	Low	Medium	High	High-Low	*p*-value
Introduction	-0.778	-0.473	-0.653	0.125	(0.719)
Growth	0.093	0.284	0.135	0.042	(0.778)
Mature	0.458	0.312	0.539	0.080	(0.560)
Shake-Out	0.015	0.076	0.431	0.416	(0.105)
Decline	0.128	0.307	0.459	0.331	(0.445)
Mature - Introduction	1.236	0.785	1.192	-0.044	(0.910)
p-value	(0.000)	(0.006)	(0.000)		

TABLE OA-6 (Continued)

Panel C: FF5 adjusted returns

	Residual Institutional Ownership				
Small stocks	Low	Medium	High	High-Low	*p*-value
Introduction	-0.621	0.380	0.210	0.832	(0.000)
Growth	0.291	0.115	0.082	-0.209	(0.170)
Mature	0.512	0.498	0.372	-0.140	(0.324)
Shake-Out	0.248	0.773	0.715	0.467	(0.113)
Decline	-0.160	0.813	0.245	0.405	(0.222)
Mature - Introduction	1.133	0.118	0.162	-0.971	(0.000)
p-value	(0.000)	(0.589)	(0.480)		
Big stocks	Low	Medium	High	High-Low	*p*-value
Introduction	-0.291	-0.218	-0.413	-0.122	(0.749)
Growth	0.235	0.349	0.182	-0.054	(0.745)
Mature	0.285	0.149	0.380	0.095	(0.497)
Shake-Out	-0.004	0.030	0.304	0.308	(0.286)
Decline	0.373	0.754	0.590	0.216	(0.635)
Mature - Introduction	0.576	0.366	0.792	0.216	(0.605)
p-value	(0.084)	(0.188)	(0.001)		

Panel D: *Q*-factor adjusted returns

	Residual Institutional Ownership				
Small stocks	Low	Medium	High	High-Low	*p*-value
Introduction	-0.420	0.610	0.624	1.044	(0.000)
Growth	0.437	0.279	0.252	-0.185	(0.257)
Mature	0.600	0.568	0.467	-0.133	(0.400)
Shake-Out	0.463	0.823	0.833	0.370	(0.267)
Decline	0.070	1.074	0.427	0.357	(0.342)
Mature - Introduction	1.020	-0.043	-0.158	-1.177	(0.000)
p-value	(0.000)	(0.879)	(0.516)		
Big stocks	Low	Medium	High	High-Low	*p*-value
Introduction	-0.287	-0.034	-0.414	-0.127	(0.749)
Growth	0.249	0.415	0.165	-0.084	(0.575)
Mature	0.375	0.194	0.376	0.001	(0.994)
Shake-Out	0.095	0.036	0.286	0.191	(0.506)
Decline	0.692	0.831	0.652	-0.039	(0.934)
Mature - Introduction	0.661	0.228	0.790	0.129	(0.770)
p-value	(0.101)	(0.437)	(0.002)		

The table presents average monthly stock returns (in percent) of portfolios sorted independently on firm life cycle and residual institutional ownership (RI). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. The results are reported separately for small and big stocks. Stocks are first classified into small and big based on the median market capitalization (obtained three months after fiscal year-end); within these groups, stocks are subsequently sorted into portfolios based on firm life cycle and RI. Residual institutional ownership is obtained at least one quarter prior fiscal year-end and is orthogonalized with respect to size and size-squared (Nagel, 2005). Panel A reports raw portfolio returns, Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors (FF3), Panel C reports intercepts from regressions of portfolio returns on the five Fama and French (2015) factors (FF5) and Panel D reports intercepts from regressions of portfolio returns on the Hou et al. (2015) *q*-factors. Portfolio returns are value-weighted (VW). The time period runs from July 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-7

Limits to arbitrage proxied by idiosyncratic volatility (RW)

Panel A: FF5 adjusted returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.404	-0.339	-0.505	-0.102	(0.708)
Growth	0.145	0.129	0.006	-0.138	(0.480)
Mature	0.256	0.451	0.603	0.347	(0.078)
Shake-Out	0.317	0.383	0.620	0.303	(0.222)
Decline	-0.440	0.488	0.221	0.660	(0.046)
Mature - Introduction	0.659	0.790	1.108	0.449	(0.047)
p-value	(0.000)	(0.000)	(0.000)		

Panel B: *Q*-factor adjusted returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.411	-0.054	-0.161	0.250	(0.411)
Growth	0.195	0.290	0.391	0.196	(0.333)
Mature	0.326	0.581	0.896	0.571	(0.009)
Shake-Out	0.376	0.508	0.996	0.619	(0.024)
Decline	-0.402	0.777	0.648	1.050	(0.005)
Mature - Introduction	0.736	0.636	1.057	0.321	(0.230)
p-value	(0.000)	(0.000)	(0.000)		

The table presents average monthly stock returns (in percent) of portfolios sorted independently on firm life cycle and idiosyncratic return volatility (IdioRisk). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Idiosyncratic volatility is calculated as the standard deviation of residuals obtained from a regression of daily stock returns on the CRSP value-weighted market return over the 12 months ending three months after fiscal year-end. Panel A presents intercepts from regressions of portfolio returns on the five Fama and French (2015) factors (FF5) and Panel B presents intercepts from regressions of portfolio returns on the Hou et al. (2015) *q*-factors. Portfolio returns are prior period gross return-weighted (RW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-8

Limits to arbitrage proxied by idiosyncratic volatility (VW)

Panel A: Raw returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	0.726	0.454	-0.008	-0.735	(0.109)
Growth	0.897	0.933	1.012	0.115	(0.784)
Mature	0.947	1.523	1.099	0.152	(0.669)
Shake-Out	0.765	1.208	1.055	0.290	(0.492)
Decline	1.010	1.182	1.126	0.116	(0.813)
Mature - Introduction	0.221	1.068	1.108	0.887	(0.031)
p-value	(0.502)	(0.000)	(0.001)		

Panel B: FF3 adjusted returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.026	-0.500	-1.083	-1.057	(0.005)
Growth	0.248	-0.038	-0.158	-0.406	(0.123)
Mature	0.388	0.625	0.045	-0.343	(0.114)
Shake-Out	0.137	0.224	-0.044	-0.181	(0.526)
Decline	0.289	0.264	0.004	-0.285	(0.432)
Mature - Introduction	0.414	1.125	1.128	0.714	(0.088)
p-value	(0.166)	(0.000)	(0.000)		

Panel C: FF5 adjusted returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	0.151	-0.251	-0.383	-0.534	(0.141)
Growth	0.228	0.268	0.395	0.167	(0.477)
Mature	0.211	0.718	0.239	0.028	(0.901)
Shake-Out	-0.029	0.494	0.320	0.349	(0.217)
Decline	0.071	0.632	0.591	0.520	(0.134)
Mature - Introduction	0.060	0.969	0.622	0.562	(0.186)
p-value	(0.845)	(0.000)	(0.035)		

TABLE OA-8 (Continued)

Panel D: *Q*-factor adjusted returns

	Past Idiosyncratic Volatility				
	Low	Medium	High	High-Low	*p*-value
Introduction	-0.104	-0.255	-0.035	0.069	(0.874)
Growth	0.245	0.347	0.426	0.180	(0.548)
Mature	0.256	0.727	0.387	0.131	(0.528)
Shake-Out	-0.101	0.538	0.157	0.259	(0.424)
Decline	0.289	1.101	0.598	0.309	(0.474)
Mature - Introduction	0.360	0.982	0.422	0.062	(0.901)
p-value	(0.188)	(0.001)	(0.254)		

The table presents average monthly stock returns (in percent) of portfolios sorted independently on firm life cycle and idiosyncratic return volatility (IdioRisk). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Idiosyncratic volatility is calculated as the standard deviation of residuals obtained from a regression of daily stock returns on the CRSP value-weighted market return over the 12 months ending three months after fiscal year-end. Panel A reports raw portfolio returns, Panel B reports intercepts from regressions of portfolio returns on the three Fama and French (1993) factors (FF3), Panel C reports intercepts from regressions of portfolio returns on the five Fama and French (2015) factors (FF5) and Panel D reports intercepts from regressions of portfolio returns on the Hou et al. (2015) *q*-factors. Portfolio returns are prior period gross return-weighted (RW). The time period runs from April 1990 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-9

Excess returns around earnings announcement dates

Panel A: Market-model

	Window (-1, +1)			Window (-3, +3)			Window (-5, +5)		
	Mean	*t*-test	*p*-value	Mean	*t*-test	*p*-value	Mean	*t*-test	*p*-value
Introduction	-0.026	-6.886	(0.000)	-0.038	-6.021	(0.000)	-0.046	-5.548	(0.000)
Growth	0.006	2.749	(0.010)	0.002	0.617	(0.542)	0.000	0.031	(0.976)
Mature	0.008	3.334	(0.002)	0.006	1.970	(0.059)	0.003	0.953	(0.349)
Shake-Out	0.005	1.708	(0.099)	-0.002	-0.573	(0.571)	-0.008	-1.580	(0.125)
Decline	-0.023	-5.685	(0.000)	-0.034	-5.791	(0.000)	-0.042	-5.834	(0.000)
Mature - Introduction	0.034	7.761	(0.000)	0.044	6.243	(0.000)	0.049	5.423	(0.000)

Panel B: Fama and French (1993) three-factor model

	Window (-1, +1)			Window (-3, +3)			Window (-5, +5)		
	Mean	*t*-test	*p*-value	Mean	*t*-test	*p*-value	Mean	*t*-test	*p*-value
Introduction	-0.025	-6.550	(0.000)	-0.038	-5.851	(0.000)	-0.046	-5.218	(0.000)
Growth	0.006	3.468	(0.002)	0.003	1.035	(0.310)	0.001	0.189	(0.851)
Mature	0.009	3.737	(0.001)	0.007	2.597	(0.015)	0.004	1.501	(0.144)
Shake-Out	0.005	2.016	(0.053)	-0.002	-0.619	(0.541)	-0.008	-1.896	(0.068)
Decline	-0.022	-5.624	(0.000)	-0.032	-6.111	(0.000)	-0.039	-5.865	(0.000)
Mature - Introduction	0.034	7.708	(0.000)	0.045	6.469	(0.000)	0.050	5.443	(0.000)

The table presents mean excess earnings announcement returns across portfolios formed on the basis of firm life cycle. For each firm in a portfolio, I calculate excess buy-and-hold returns in the [-1, +1], [-3, +3] and [-5, +5] event windows centered on the quarterly earnings announcement date. I then aggregate these returns over the four quarters following fiscal year-end. In Panel A, excess returns are calculated using the market model with parameters estimated over a period of 200 days ending 10 days before the beginning of the event window. In Panel B, excess returns are calculated using the Fama and French (1993) three-factor model with parameters estimated over a period of 200 days ending 10 days before the beginning of the event window. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. The sample period runs from 1989 to 2017, so that earnings announcement returns over the *four* subsequent quarters are available in each year. All variables are defined in the Appendix of the paper.

TABLE OA-10
Dynamic risk on earnings announcement dates

	Window [-1, +1]	Window [-3, +3]	Window [-5, +5]
Introduction × Eday	-0.161	-0.072	-0.044
	(0.000)	(0.000)	(0.001)
Growth × Eday	0.105	0.071	0.063
	(0.000)	(0.000)	(0.000)
Mature × Eday	0.116	0.067	0.054
	(0.000)	(0.000)	(0.000)
Shake-Out × Eday	0.095	0.049	0.037
	(0.000)	(0.001)	(0.001)
Decline × Eday	-0.131	-0.057	-0.023
	(0.001)	(0.022)	(0.230)
Introduction × Market (M)	0.064	0.060	0.063
	(0.002)	(0.003)	(0.003)
Growth × Market (M)	0.137	0.136	0.139
	(0.000)	(0.000)	(0.000)
Mature × Market (M)	-0.033	-0.034	-0.030
	(0.175)	(0.171)	(0.221)
Shake-Out × Market (M)	-0.025	-0.026	-0.023
	(0.285)	(0.268)	(0.328)
Decline × Market (M)	-	-	-
	-	-	-
Introduction × Eday × M	0.070	0.066	0.059
	(0.030)	(0.005)	(0.006)
Growth × Eday × M	0.081	0.047	0.041
	(0.000)	(0.000)	(0.000)
Mature × Eday × M	0.045	0.025	0.025
	(0.001)	(0.016)	(0.009)
Shake-Out × Eday × M	0.036	0.027	0.029
	(0.205)	(0.161)	(0.082)
Decline × Eday × M	0.068	0.032	0.050
	(0.239)	(0.293)	(0.046)
Intercept + Introduction	-0.117	-0.028	0.000
+ Introduction × *Eday*	(0.000)	(0.082)	(0.967)
Intercept + Mature +	0.199	0.148	0.133
Mature × Eday	(0.000)	(0.000)	(0.000)
Adj. R2	0.072	0.072	0.072
Controls	Yes	Yes	Yes
Fixed Effects	Day	Day	Day
Cluster	Firm-day	Firm-day	Firm-day

The table presents results from regressing daily returns (in percent) on firm life cycle stage indicators (unreported), interactions between firm life cycle indicators and earnings day indicators (*Eday*), further interactions between firm life cycle indicators and the value-weighted market index (M), and control variables (unreported). Following Asparouhova et al. (2010), regressions are weighted by prior period gross returns (RW). Introduction, Growth, Mature, Shake-out, Decline are (0, 1) dummies equal to one when a firm-day belongs to the corresponding life cycle stage and zero otherwise. *Eday* is a (0,1) dummy variable equal to one over the three-day, seven-day or eleven-day window around an earnings announcement date. The control variables include age, log book-to-market, log market capitalization, market beta, idiosyncratic volatility, illiquidity, momentum, reversal, asset growth, operating profitability, accruals, R&D intensity, patent intensity, patent citation impact, 10 lagged values of the daily return, 10 lagged values of the daily squared return and 10 lagged values of the daily trading volume. The sample is based on 25,696,595 daily observations covering the period 199004–201912. Standard errors are clustered by firm and day. All variables are defined in the Appendix of the paper.

TABLE OA-11

RW hedge portfolio strategies – subsample analysis

Panel A: Time period 199004 - 201108

	Raw returns			FF3 adjusted returns		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	-0.116	-0.182	(0.856)	-0.920	-3.741	(0.000)
Growth	0.933	2.204	(0.028)	0.189	1.665	(0.097)
Mature	1.319	3.787	(0.000)	0.639	6.982	(0.000)
Shake-Out	1.317	2.959	(0.003)	0.554	4.444	(0.000)
Decline	0.855	1.236	(0.217)	0.019	0.062	(0.951)
Mature - Introduction	1.435	3.626	(0.000)	1.559	6.649	(0.000)

Panel B: Time period 201109 - 201912

	Raw returns			FF3 adjusted returns		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	0.192	0.301	(0.764)	-1.069	-2.642	(0.010)
Growth	0.907	2.089	(0.039)	-0.245	-1.939	(0.055)
Mature	1.115	3.040	(0.003)	0.076	0.952	(0.344)
Shake-Out	1.052	2.533	(0.013)	0.011	0.072	(0.943)
Decline	0.400	0.617	(0.539)	-0.943	-2.374	(0.020)
Mature - Introduction	0.923	2.132	(0.035)	1.145	2.701	(0.008)

The table presents average monthly stock returns (in percent) of five portfolios formed on the basis of firm life cycle. It reports both raw portfolio returns and portfolio returns adjusted for the three Fama and French (1993) factors (FF3). Long/short positions are taken in each month on mature/introduction firms, allowing for a three-month lag between fiscal year-end and portfolio formation date. Portfolio returns are prior period gross return-weighted (RW). Panel A reports results for the period April 1990 to August 2011 and Panel B reports results for the period September 2011 to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-12

VW hedge portfolio strategies – subsample analysis

Panel A: Time period 199004 - 201108

	Raw returns			FF3 adjusted returns		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	0.032	0.056	(0.955)	-0.698	-3.910	(0.000)
Growth	0.768	2.180	(0.030)	0.248	3.395	(0.001)
Mature	0.939	3.810	(0.000)	0.524	7.827	(0.000)
Shake-Out	0.641	1.961	(0.051)	0.096	0.714	(0.476)
Decline	0.872	1.547	(0.123)	0.085	0.374	(0.709)
Mature - Introduction	0.907	2.126	(0.034)	1.222	6.044	(0.000)

Panel B: Time period 201109 - 201912

	Raw returns			FF3 adjusted returns		
	Mean	*t*-stat	*p*-value	Mean	*t*-stat	*p*-value
Introduction	0.909	1.429	(0.156)	-0.403	-0.962	(0.339)
Growth	1.198	3.564	(0.001)	-0.010	-0.091	(0.927)
Mature	1.144	4.086	(0.000)	0.033	0.574	(0.567)
Shake-Out	1.290	3.788	(0.000)	0.069	0.493	(0.623)
Decline	1.374	2.127	(0.036)	-0.108	-0.312	(0.756)
Mature - Introduction	0.235	0.461	(0.646)	0.436	0.955	(0.342)

The table presents average monthly stock returns (in percent) of five portfolios formed on the basis of firm life cycle. It reports both raw portfolio returns and portfolio returns adjusted for the three Fama and French (1993) factors (FF3). Long/short positions are taken in each month on mature/introduction firms, allowing for a three-month lag between fiscal year-end and portfolio formation date. Portfolio returns are value-weighted (VW). Panel A reports results for the period April 1990 to August 2011 (257 months) and Panel B reports results for the period September 2011 to December 2019 (100 months). *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-13

Firm-level regressions – subsample analysis

Panel A: Time period 199004 - 201108

	RW		VW	
	1	2	1	2
Introduction	-0.116	0.537	0.032	0.523
	(0.856)	(0.280)	(0.955)	(0.283)
Growth	0.933	1.031	0.768	0.968
	(0.028)	(0.023)	(0.030)	(0.044)
Mature	1.319	1.288	0.939	1.107
	(0.000)	(0.003)	(0.000)	(0.016)
Shake-Out	1.317	1.269	0.641	0.901
	(0.003)	(0.006)	(0.051)	(0.061)
Decline	0.855	0.932	0.872	1.009
	(0.217)	(0.062)	(0.123)	(0.049)
Controls	No	Yes	No	Yes
Mature - Introduction	1.435	0.751	0.907	0.584
	(0.000)	(0.000)	(0.034)	(0.013)
Adj. R2	0.104	0.150	0.177	0.313

Panel B: Time period 201109 - 201912

	RW		VW	
	1	2	1	2
Introduction	0.192	0.454	0.909	0.605
	(0.764)	(0.331)	(0.156)	(0.257)
Growth	0.907	0.874	1.198	1.152
	(0.039)	(0.056)	(0.001)	(0.014)
Mature	1.115	0.918	1.144	0.973
	(0.003)	(0.030)	(0.000)	(0.032)
Shake-Out	1.052	1.086	1.290	1.056
	(0.013)	(0.012)	(0.000)	(0.025)
Decline	0.400	(0.565)	1.374	1.047
	(0.539)	(0.247)	(0.036)	(0.111)
Controls	No	Yes	No	Yes
Mature - Introduction	0.923	0.464	0.235	0.368
	(0.035)	(0.056)	(0.646)	(0.292)
Adj. R2	0.087	0.135	0.179	0.313

The table reports results from Fama-MacBeth regressions of future monthly firm-level stock returns (in percent) on firm life cycle stage indicators and control variables (unreported). Firm life cycle indicators are obtained monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Introduction, Growth, Mature, Shake-out and Decline are (0, 1) dummies that take the value of one if the firm belongs to the corresponding life cycle stage and zero otherwise. The control variables include age (*age*), log book-to-market (*logBP*), log market capitalization (*logME*), market beta (β), idiosyncratic volatility (*IdioRisk*), illiquidity (*Illiquidity*), momentum ($Ret^{2\text{-}12}$), reversal (Ret^{1}), asset growth (*AGR*), operating profitability (*OP*), accruals (*ACC*), R&D intensity (*R&D*), patent intensity (*Patent*) and patent citation impact (*Citation*). Following Asparouhova et al. (2010), I use two weighting schemes; prior period gross return-weighting (RW) and value-weighting (VW). Panel A reports results for the period April 1990 to August 2011 (257 months) and Panel B reports results for the period September 2011 to December 2019 (100 months). *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. Reported R2s are time-series means of monthly adjusted R2s. All variables are defined in the Appendix of the paper.

TABLE OA-14

Double sort with institutional ownership (RW) – subsample analysis

Panel A: Time period 199004 – 201108

Raw returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.670	0.897	0.758	-0.912	(0.001)
p-value	(0.000)	(0.018)	(0.020)		

FF3 adjusted returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.868	1.047	0.856	-1.012	(0.000)
p-value	(0.000)	(0.000)	(0.000)		

Panel B: Time period 201109 - 201912

Raw returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.320	0.241	0.102	-1.217	(0.002)
p-value	(0.009)	(0.601)	(0.809)		

FF3 adjusted returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.713	0.374	0.149	-1.565	(0.000)
p-value	(0.000)	(0.406)	(0.732)		

The table presents average monthly stock returns (in percent) of long-short portfolios formed on the basis of firm life cycle conditional on residual institutional ownership (RI). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Residual institutional ownership is obtained at least one quarter prior fiscal year-end and is orthogonalized with respect to size and size-squared. Results show both raw portfolio returns and portfolio returns adjusted for the three Fama and French (1993) factors (FF3). Portfolio returns are prior period gross return-weighted (RW). Panel A reports results for the period April 1990 to August 2011 (257 months) and Panel B reports results for the period September 2011 to December 2019 (100 months). *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-15

Double sort with institutional ownership (small stocks, VW) – subsample analysis

Panel A: Time period 199004 – 201108

Raw returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.635	0.881	0.455	-1.179	(0.000)
p-value	(0.000)	(0.025)	(0.144)		

FF3 adjusted returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.952	1.090	0.769	-1.183	(0.000)
p-value	(0.000)	(0.000)	(0.003)		

Panel B: Time period 201109 - 201912

Raw returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	0.704	-0.525	-0.070	-0.774	(0.088)
P-Value	(0.185)	(0.308)	(0.893)		

FF3 adjusted returns	Residual Institutional Ownership				
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.629	0.495	0.447	-1.182	(0.009)
p-value	(0.001)	(0.291)	(0.385)		

The table presents average monthly stock returns (in percent) of long-short portfolios formed on the basis of firm life cycle conditional on residual institutional ownership (RI). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Results are reported only for small stocks – stocks with market capitalization below the median value. Residual institutional ownership is obtained at least one quarter prior fiscal year-end and is orthogonalized with respect to size and size-squared. Market capitalisation is obtained three months after fiscal year-end. Results show both raw portfolio returns and portfolio returns adjusted for the three Fama and French (1993) factors (FF3). Portfolio returns are value-weighted (VW). Panel A reports results for the period April 1990 to August 2011 (257 months) and Panel B reports results for the period September 2011 to December 2019 (100 months). *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-16

Double sort with idiosyncratic volatility (RW) – subsample analysis

Panel A: Time period 199004 – 201108

Raw returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	0.967	1.368	1.884	0.917	(0.004)
p-value	(0.000)	(0.000)	(0.000)		

FF3 adjusted returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	1.044	1.397	1.854	0.810	(0.002)
p-value	(0.000)	(0.000)	(0.000)		

Panel B: Time period 201109 - 201912

Raw returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	0.552	0.193	0.716	0.164	(0.760)
p-value	(0.048)	(0.522)	(0.138)		

FF3 adjusted returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	0.272	0.215	0.944	0.673	(0.190)
p-value	(0.348)	(0.478)	(0.061)		

The table presents average monthly stock returns (in percent) of long-short portfolios formed on the basis of firm life cycle conditional on idiosyncratic return volatility (IdioRisk). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Idiosyncratic volatility is calculated as the standard deviation of residuals obtained from a regression of daily stock returns on the CRSP value-weighted market return over the 12 months ending three months after fiscal year-end. Results show both raw portfolio returns and portfolio returns adjusted for the three Fama and French (1993) factors (FF3). Portfolio returns are prior period gross return-weighted (RW). Panel A reports results for the period April 1990 to August 2011 (257 months) and Panel B reports results for the period September 2011 to December 2019 (100 months). *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-17

Double sort with idiosyncratic volatility (VW) – subsample analysis

Panel A: Time period 199004 – 201108

Raw returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	0.417	1.471	1.475	1.058	(0.031)
p-value	(0.325)	(0.000)	(0.000)		

FF3 adjusted returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	0.574	1.592	1.414	0.840	(0.091)
p-value	(0.124)	(0.000)	(0.000)		

Panel B: Time period 201109 - 201912

Raw returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	-0.283	0.033	0.163	0.446	(0.551)
p-value	(0.517)	(0.946)	(0.807)		

FF3 adjusted returns			Idiosyncratic Volatility		
	Low	Medium	High	High-Low	*p*-value
Mature - Introduction	-0.549	-0.264	0.296	0.845	(0.271)
p-value	(0.201)	(0.615)	(0.685)		

The table presents average monthly stock returns (in percent) of long-short portfolios formed on the basis of firm life cycle conditional on idiosyncratic return volatility (IdioRisk). Portfolios are formed monthly, allowing for a three-month lag between fiscal year-end and portfolio formation date. Idiosyncratic volatility is calculated as the standard deviation of residuals obtained from a regression of daily stock returns on the CRSP value-weighted market return over the 12 months ending three months after fiscal year-end. Results show both raw portfolio returns and portfolio returns adjusted for the three Fama and French (1993) factors (FF3). Portfolio returns are value-weighted (VW). Panel A reports results for the period April 1990 to August 2011 (257 months) and Panel B reports results for the period September 2011 to December 2019 (100 months). *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-18

Quantile regressions

Panel A: Time period 1989–2010

	5%	10%	25%	40%	50%	60%	75%	90%	95%	OLS	IQR	SKEW
Introduction	-1.100	-0.627	-0.189	0.012	0.118	0.241	0.542	1.396	2.680	0.305	2.023	0.264
	(0.000)	(0.000)	(0.000)	(0.320)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Mature	-0.296	-0.173	-0.039	0.024	0.056	0.092	0.162	0.327	0.501	0.086	0.500	0.083
	(0.000)	(0.000)	(0.006)	(0.036)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Mature - Introduction	0.804	0.454	0.151	0.011	-0.062	-0.149	-0.380	-1.069	-2.179	-0.219	-1.523	0.181
p-value	(0.000)	(0.000)	(0.000)	(0.196)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
R2	0.098	0.057	0.017	0.007	0.008	0.015	0.036	0.088	0.138	0.015	NA	

Panel B: Time period 2011–2018

	5%	10%	25%	40%	50%	60%	75%	90%	95%	OLS	IQR	SKEW
Introduction	-1.341	-0.764	-0.227	-0.025	0.073	0.177	0.419	1.189	2.139	0.197	1.953	0.143
	(0.000)	(0.000)	(0.000)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Mature	-0.285	-0.152	-0.039	0.010	0.036	0.062	0.111	0.221	0.343	0.042	0.374	-0.010
	(0.000)	(0.000)	(0.001)	(0.055)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	
Mature - Introduction	1.056	0.612	0.188	0.035	-0.036	-0.115	-0.308	-0.968	-1.796	-0.155	-1.579	0.153
p-value	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
R2	0.131	0.079	0.023	0.008	0.009	0.015	0.040	0.105	0.160	0.012	NA	

The table reports results from Fama-MacBeth quantile and OLS regressions of earnings growth in year $t+1$ (EGR_{t+1}) on firm life cycle stage indicators in year t. Introduction, Growth, Mature, Shake-out, Decline are (0, 1) dummies that take the value of one when a firm-year belongs to the corresponding life cycle stage and zero otherwise. Quantile regressions are estimated for quantiles in the set $\tau \in \{0.05, 0.10, 0.25, 0.40, 0.50, 0.60, 0.75, 0.90, 0.95\}$. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. Reported R2s are time-series means of annual pseudo (adjusted) R2s for quantile (OLS) regressions. Q_τ denotes the estimated τ'th quantile of EGR_{t+1} conditional on firm life cycle. *IQR* is a measure of uncertainty in EGR_{t+1}, defined as $Q_{90} - Q_{10}$. *SKEW* is a measure of skewness in EGR_{t+1}, defined as $(Q_{90} - Q_{10} - 2\times Q_{50})/IQR$. Panel A reports results for the period 1989–2010 and Panel B reports results for the period 2011–2018. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-19

Analysts' forecast errors three months after fiscal year-end – subsample analysis

Panel A: Time period 1989–2010

	Mean	*t*-stat	*p*-value
Introduction	-0.045	-9.147	(0.000)
Growth	-0.015	-7.031	(0.000)
Mature	-0.009	-5.135	(0.000)
Shake-Out	-0.019	-5.395	(0.000)
Decline	-0.036	-3.804	(0.001)
Mature - Introduction	0.036	9.156	(0.000)

Panel B: Time period 2011–2018

	Mean	*t*-stat	*p*-value
Introduction	-0.023	-4.008	(0.005)
Growth	-0.005	-3.789	(0.007)
Mature	-0.004	-3.654	(0.008)
Shake-Out	-0.006	-2.293	(0.056)
Decline	-0.003	-0.513	(0.624)
Mature - Introduction	0.019	3.721	(0.007)

The table reports mean signed analysts' forecast errors for five portfolios formed on the basis of firm life cycle. Analysts' forecasts are obtained three months after fiscal year-end. Panel A reports results for the period 1989–2010 and Panel B reports results for the period 2011–2018. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.

TABLE OA-20

Analysts' forecast errors over time

Panel A: Time period 1989–2010

Month	*All Observations*	Introduction	Mature	Mature - Introduction	*t*-stat	*p*-value
1	-0.021	-0.053	-0.010	0.043	8.379	0.000
2	-0.019	-0.050	-0.009	0.041	8.303	0.000
3	-0.018	-0.045	-0.008	0.037	7.330	0.000
4	-0.016	-0.042	-0.008	0.034	7.169	0.000
5	-0.015	-0.038	-0.007	0.031	7.265	0.000
6	-0.012	-0.032	-0.006	0.027	6.546	0.000
7	-0.011	-0.029	-0.005	0.024	6.309	0.000
8	-0.009	-0.026	-0.004	0.022	6.964	0.000
9	-0.007	-0.022	-0.003	0.019	7.549	0.000
10	-0.006	-0.020	-0.002	0.018	7.734	0.000
11	-0.006	-0.019	-0.002	0.017	7.578	0.000

Panel B: Time period 2011–2018

Month	*All Observations*	Introduction	Mature	Mature - Introduction	*t*-stat	*p*-value
1	-0.006	-0.020	-0.004	0.016	2.240	0.060
2	-0.005	-0.015	-0.004	0.011	1.660	0.141
3	-0.004	-0.009	-0.004	0.006	0.930	0.383
4	-0.004	-0.010	-0.003	0.006	1.167	0.281
5	-0.003	-0.008	-0.003	0.005	0.914	0.391
6	-0.002	-0.007	-0.002	0.005	1.580	0.158
7	-0.002	-0.008	-0.002	0.006	1.843	0.108
8	-0.002	-0.008	-0.001	0.007	2.732	0.029
9	-0.001	-0.006	0.000	0.005	3.386	0.012
10	-0.001	-0.006	0.000	0.006	3.232	0.014
11	0.000	-0.004	0.000	0.005	1.304	0.233

The table reports mean signed analysts' forecast errors for introduction firms, mature firms and the full sample. Forecast errors are shown for the 11 months following the current year's earnings announcement and leading up to the next year's earnings announcement. Panel A reports results for the period 1989–2010 and Panel B reports results for the period 2011–2018, with analysts' forecast errors being tracked up to December 2019. *P*-values in parentheses correspond to Newey-West standard errors with 1 lag. All variables are defined in the Appendix of the paper.