Factor Investing and Firm Life Cycle: A Contextual Approach

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KEY FINDINGS

- This study investigates a contextual modeling approach in factor investing by applying the firm life-cycle theory.
- Risk premiums differ across different life-cycle stages.
- Conditioning factor strategies on firm life cycle improves the efficacy of harvesting risk premiums.

ABSTRACT

This study investigates a contextual modeling approach in factor investing by applying the firm life-cycle theory. The authors' findings indicate that factor risk premiums are different across firm life-cycle stages. The size and value risk premiums are largest for introductory- and decline-stage firms, whereas the profitability risk premium is driven by mature and shakeout firms. The momentum risk premium originates in intro and growth firms. The authors show that conditioning factor strategies on firm life cycle improves the efficacy of harvesting risk premiums and allows for risk factor arbitrage. The study concludes that firm life cycle matters for factor investing.

The firm life-cycle concept is pivotal for comprehending how companies evolve over time. From inception through maturity and possibly decline, firms experience profound structural changes that reshape their strategies and risk-taking behaviors (Quinn and Cameron 1983; Miller and Friesen 1984). Extensive research has explored the implications of firm life-cycle stages on corporate finance and accounting (Dickinson 2011; Vorst and Yohn 2018; Cantrell and Dickinson 2020). Recent studies have also highlighted practitioners' growing interest in applying life-cycle stages to capital allocation and stock valuations (Mauboussin and Callahan 2023). Yet, there remains a significant gap in understanding how the firm life-cycle concept relates to factor investing. This study seeks to address this gap by adopting a contextual modeling approach (Sorensen, Hua, and Qian 2005) using the firm life-cycle theory as a framework. Specifically, we investigate how the five-factor model by Fama and French (2015a, b), augmented with the momentum factor, aligns with different stages of a firm's life cycle and explore its potential to improve the harvesting of risk premiums. This approach offers a nuanced and potentially more effective alternative to traditional one-size-fits-all models.

Using a sample of 13,534 distinct US firms from 1989 until 2022, we follow the methodology of Dickinson (2011) in classifying firms into five life-cycle phases according to their cash flow patterns: 1) introduction, 2) growth, 3) mature, 4) shakeout, and 5) decline. We then examine the performance of portfolios formed by life-cycle stage.

Our results provide interesting insights into the interplay between a firm's life-cycle stages and factor investing. First, investors holding mature firms stand to gain higher buy-and-hold returns, accompanied by the least volatility in their portfolios and yielding the highest Sharpe ratio of 0.71 out of all firm life-cycle portfolios. Second, we identify that the robust performance of mature firms can be attributed to their exposure to the profitability and investment factors, providing insights into the driving forces behind their financial success. At the same time, mature firms seem to carry less systematic risk than the market and hedge against size and value risk. Third, we analyze factor risk premiums across different life-cycle stages. Our examination reveals that these risk premiums exhibit noteworthy variations based on the stage of a firm's life cycle. For instance, the size and value risk premiums emerge as most pronounced for firms in the introduction and decline stages. The profitability risk premium finds its roots in mature and shakeout firms, while the momentum risk premium is exclusively driven by intro and growth firms. These distinctive patterns spotlight the relationship between factor risk premiums and a firm's life-cycle stage, thereby paving the way for nuanced investment strategies. Fourth, we use risk premiums to calculate out-of-sample expected returns and show that they can be exploited more efficiently by incorporating life-cycle information. Specifically, we compare an unconditional strategy with a strategy that estimates risk premiums conditional on firm life cycle and find that the conditional long–short portfolio outperforms the unconditional one by 0.32% a month (approximately 3.9% a year). This is a relative performance improvement of about 70%.

We are agnostic about the reason for the difference in risk premia across life cycles. However, we believe that one potential source could be the mispricing of cash flows and accruals at different life-cycle stages, as documented in Hribar and Yehuda (2015).

This study carries significant implications for both academia and practitioners. By exploring the interplay between factor models and firm life-cycle stages, we seek to enhance our understanding of the multifaceted relationship between factors used in asset pricing and the dynamic evolution of firms. Our findings offer insights into refining factor models to account for the varying risk profiles and financial behaviors exhibited by firms at different life-cycle phases.

In several important ways, our study is fundamentally distinct from the concurrent study by Konstantinidi (2022), which also explores portfolio returns based on the firm life cycle. First, Konstantinidi does not focus on factor investing or the efficacy of harvesting risk premiums. Specifically, she does not estimate risk premiums conditional on life-cycle stages. Nevertheless, her analysis on analysts' forecast errors supports our assumption that differences in expectations could play a role for the differences in risk premiums. Second and contrary to our study, Konstantinidi finds significant monthly alphas in many portfolios created based on life-cycle stages. We do not find any significant alphas in our analyses, only exposure to different risk factors.

FIRM LIFE-CYCLE THEORY

The corporate life-cycle concept from organizational science suggests that firms go through distinct stages from birth to decline, with changes in strategies and structures (Gray and Ariss 1985; Miller and Friesen 1980, 1984; Quinn and Cameron 1983). Penrose (2009) posits that growth is influenced by resources and opportunities, aligning with Chandler (1969) on the alignment of structures with growth strategies.

A firm's competitive advantage relies on valuable, rare, and inimitable resources (Barney 1991), guiding them through life-cycle stages (Helfat and Peteraf 2003; Miller and Friesen 1984; Quinn and Cameron 1983; Wernerfelt 1984). Helfat and

Peteraf (2003) introduced the dynamic resource-based theory, stating that a firm's resource base evolves, influencing its life-cycle stages. Modern studies show nonlinear progression, where firms may move between stages (Dickinson 2011).

Life-cycle stages impact management and strategy, influencing competitiveness. Accounting and finance research have developed metrics to categorize life-cycle stages, correlating with corporate decisions such as investments and tax planning (Arikan and Stulz 2016; Faff et al. 2016). Empirical studies highlight the importance of interpreting accounting information through the lens of a firm's life-cycle stage (Anthony and Ramesh 1992; Hribar and Yehuda 2015). As firms transition between stages, financial statements provide different insights into their economic conditions and prospects, affecting valuation (Cantrell and Dickinson 2020; Vorst and Yohn 2018; Dickinson 2011; Hribar and Yehuda 2015). Recent research by Dickinson, Kassa, and Schaberl (2018) shows evolving investor preferences for accounting measures based on life-cycle stage, with firms adjusting their disclosures and strategies accordingly (Chen, DeFond, and Park 2002; Cohen, Mashruwala, and Zach 2009).

DATA AND METHODOLOGY

We use firm-level data from two sources. First, we obtain stock return data from the Center for Research in Security Prices (CRSP). We focus on ordinary common shares (share code 10 or 11) that are traded on the NYSE, AMEX, or Nasdaq (exchange code 1, 2, or 3). Whenever a stock is delisted, we replace the return with the delisting return. We drop public utilities and financial firms (two-digit SIC code: 49 and 60–67, respectively).[1] Second, we obtain accounting information from the annual CRSP/Compustat Merged Database. We need accounting information for both our life-cycle classification and our empirical analysis. We assume throughout our analysis that accounting information becomes available with a lag of six months. This assumption is conservative and in line with existing studies (Fama and French 1993). Our sample spans the period from 1989 until 2022. In total, we have data on 13,534 distinct firms.

In the latter part of our analysis, we use cross-sectional Fama and MacBeth (1973) regressions. Hence, we need to construct the following variables. We calculate beta in rolling window regressions using 60 months of data. We use the market factor provided on Ken French's Data Library website (value-weighted return of all NYSE, AMEX, and Nasdaq stocks) as our market index.[2] We calculate book equity as stockholder's equity minus the redemption value of preferred stock plus balance-sheet deferred taxes. If stockholder's equity is missing, we replace it with the par value of preferred stock plus common equity or assets minus liabilities. If the redemption value of preferred stock is missing, we replace it with the liquidating value of preferred stock or the par value of preferred stock. We replace missing values of balance sheet deferred taxes with zero. We drop firms with negative book equity. This approach is in line with Fama and French (2015a, b). In addition, we calculate a measure of firm profitability by dividing revenue minus cost of goods sold minus selling, general, and administrative expenses minus interest expenses by book equity. To measure investment, we divide total assets at the end of fiscal year t by total assets at the end of fiscal $t-1$. Again, this is in line with the studies of Fama and French (2015a, b). Last but not least, we calculate past return from month $t-12$ until $t-2$ (Fama and French 2018). We Winsorize all variables at the 1% and 99% levels.

[1] We exclude financial firms due to capital constraints, which make direct comparisons with other industries less meaningful.

[2] Kenneth R. French Data Library, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

FIRM LIFE CYCLE

This section provides the framework for our empirical analysis. It is divided into two parts. First, we describe the different life-cycle stages. Using our sample of 13,534 distinct US firms from 1989 until 2022, we follow the methodology of Dickinson (2011) in classifying firms into five life-cycle phases according to their cash flow patterns:

1. introduction,
2. growth,
3. mature,
4. shakeout, and
5. decline.

Second, we provide descriptive statistics by life-cycle stage.

Life-Cycle Stages

Our life-cycle classification relies on cash flow information. In particular, we use the approach of Dickinson (2011) that utilizes cash flows from operating, investing, and financing activities. In this section, we describe in detail Dickinson's classifications, and Exhibit 1 summarizes Dickinson's approach.

Intro. Companies in an introductory stage have negative cash flows from operating activities, negative cash flows from investing activities, and positive cash flows from financing activities. This cash flow profile reflects that firms in the introductory stage, on average, lose money, try to grow their business, and rely on financing from investors and creditors. Examples of firms in an introductory stage are Uber Technologies, Alnylam Pharmaceuticals, and Coupang (as of December 2022).

Growth. Firms in the growth stage have positive cash flows from operations, and they raise capital from investors and creditors to further invest in their business. Examples of firms in a growth stage are Amazon, Nvidia, and Merck & Co (as of December 2022).

Mature. Firms in a mature stage have positive cash flows from operating activities and negative cash flows from investing and financing activities. They have a cash-generating core business, which they maintain, and they pay back the investors. Examples of firms in a mature stage are Apple, Microsoft, and Alphabet (as of December 2022).

Shakeout. Firms in a shakeout stage may show three distinct cash flow profiles. They might have negative cash flows from operating, investing, and financing activities; they might have positive cash flows from operating, investing, and financing activities; or they might have positive cash flows from operating and investing activities and

EXHIBIT 1

Firm Life Cycle and Cash Flows

Cash Flows from…	1 Intro	2 Growth	3 Mature	4 Shakeout	5 Shakeout	6 Shakeout	7 Decline	8 Decline
Operating Activities	–	+	+	–	+	+	–	–
Investing Activities	–	–	–	–	+	+	+	+
Financing Activities	+	+	–	–	+	–	+	–

NOTES: This exhibit illustrates how we use cash flows from operating, investing, and financing activities to proxy firm life-cycle stages. The classification follows Dickinson (2011). A plus sign indicates a positive cash flow to the firm and a minus sign indicates a negative cash flow to the firm.

negative cash flows from financing activities. Examples of firms in a shakeout stage are Amgen and General Electric (as of December 2022).

Decline. Firms in a decline stage might show either of two cash flow profiles. They have negative cash flows from operating activities, positive cash flows from investing activities, and either positive or negative cash flows from financing activities. Both cash flow profiles share that decline firms are losing money from their business model and that they are divesting their assets. These cash flow profiles are a consequence of declining profitability due to (potentially) outdated business models. Examples of firms in a decline stage are Boeing, Seagen, and Inspire Medical Systems (as of December 2022).

To highlight that there is within-firm variation in life-cycle stages over time, we plot the life-cycle stages of Apple and Microsoft from 1989 until 2022 in Exhibit 2. Not only do both firms change their life-cycle stage frequently, but they also change life-cycle stages nonlinearly. For instance, in the 1990s, Microsoft repeatedly switched back and forth between the growth and the mature stages. Likewise, in the 2000s, Apple switched back and forth between the growth and shakeout stages. The changing life-cycle stages might contain important information and reflect managerial decisions such as changes in leverage or divestitures.

We also look at the fraction of firms in different life-cycle stages over the business cycle. In Exhibit 3, we plot the fraction of firms within a specific life-cycle stage. We note that intro, growth, mature, shakeout, and decline firms make up approximately 18%, 28%, 37%, 9%, and 7% of all firms, respectively. Interestingly, even for our sample of publicly listed firms, there is a considerable number of firms in the intro and decline stages. We also note that there is considerable variation over time. For instance, the proportion of mature firms varies from 27% to 51%.

Descriptive Statistics

To analyze cross-sectional differences across life-cycle stages, we show descriptive statistics in Exhibit 4. We first focus on firm size. Intro firms have, on average, a market capitalization of USD 0.44 billion. Growth firms are considerably larger, with an average market capitalization of USD 2.43 billion. Mature firms have the largest market capitalization. The average market capitalization for mature firms amounts to USD 4.65 billion. Shakeout firms have an average market capitalization that is quite similar to the market capitalization of growth firms. Likewise, the market capitalization

EXHIBIT 2

Apple's and Microsoft's Life-Cycle Stages, 1989–2022

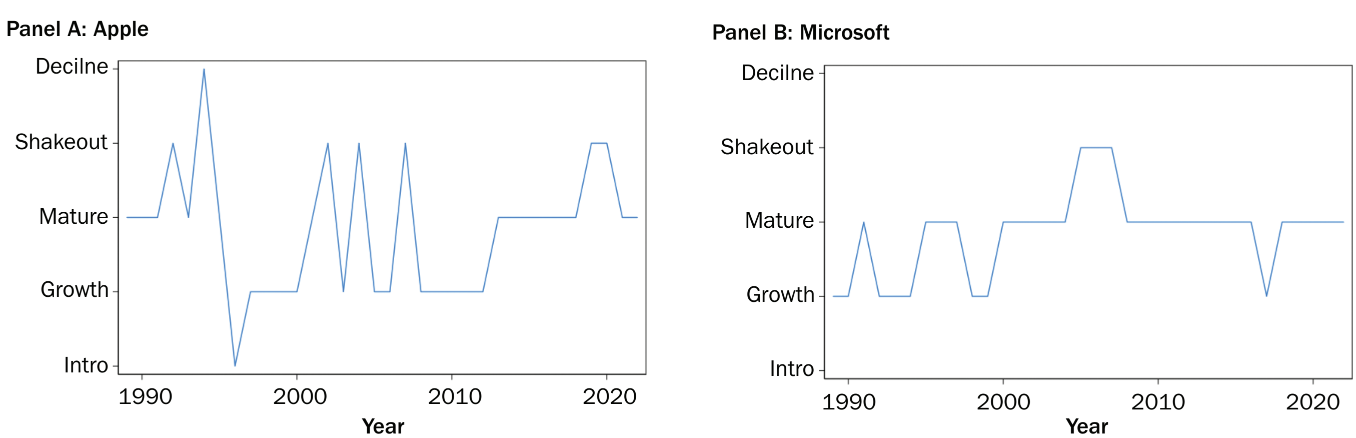
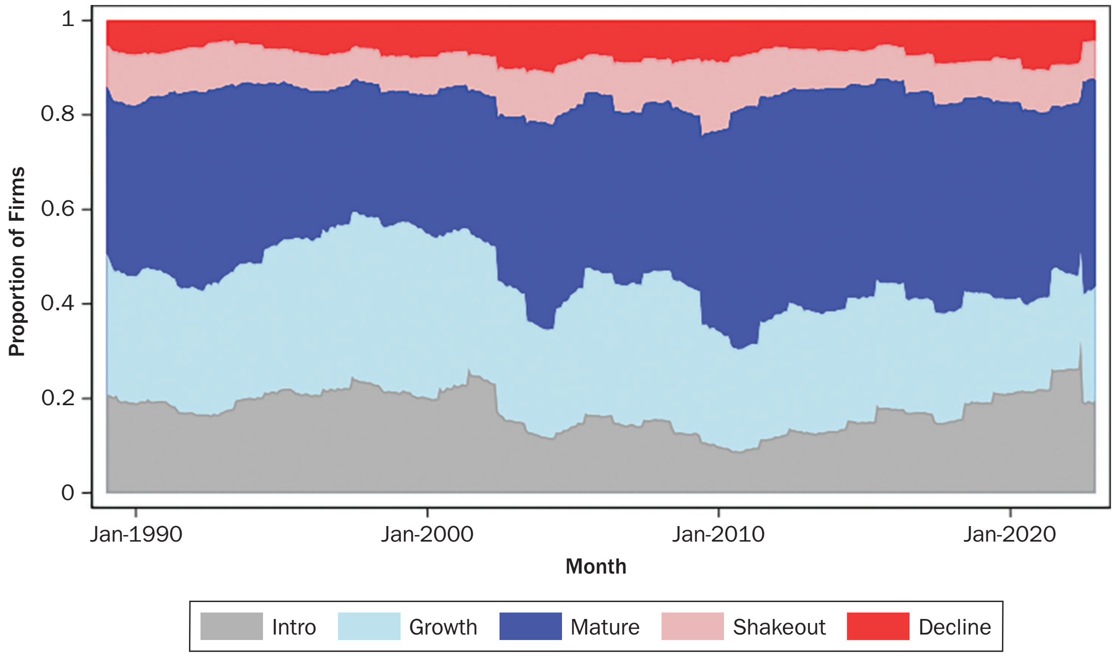


EXHIBIT 3

Life-Cycle Stages Over Time, January 1989–December 2022



NOTES: This exhibit shows the proportion of firms that are in a specific life-cycle stage. The *x*-axis denotes the month, and the *y*-axis denotes the fraction of firms in a life-cycle stage. The sample starts in January 1989 and ends in December 2022.

EXHIBIT 4

Summary Statistics

	Intro	Growth	Mature	Shakeout	Decline
Market Cap (mean)	0.44	2.43	4.65	2.43	0.42
Market Cap (SD)	2.72	10.04	15.89	11.33	2.85
Assets (mean)	0.25	1.13	2.07	1.22	0.22
Assets (SD)	1.29	3.90	7.43	4.93	1.49
Book-to-Market (mean)	0.62	0.68	0.75	0.90	0.74
Book-to-Market (SD)	0.83	0.79	0.84	1.01	0.92
Debt-to-Equity (mean)	2.57	2.13	2.25	2.74	2.41
Debt-to-Equity (SD)	6.09	6.56	7.88	7.50	6.34
Profitability (mean)	–0.42	0.28	0.36	0.13	–0.53
Profitability (SD)	1.06	0.43	0.46	0.65	1.01
Investment (mean)	0.37	0.35	0.04	–0.03	–0.05
Investment (SD)	0.81	0.54	0.21	0.38	0.54
Past Return (mean)	–0.03	0.10	0.16	0.14	0.06
Past Return (SD)	0.76	0.60	0.54	0.69	0.85

NOTES: Market cap is the total market capitalization (in USD billions). Assets is the total asset value (in USD billions) as reported by the company. Book-to-market is the book-to-market ratio. Debt-to-equity is the ratio of total liabilities to total stockholder's equity. Profitability is revenue minus cost of goods sold minus selling, general, and administrative expenses minus interest expenses divided by book equity. Investment is total assets at the end of fiscal year *t* divided by total assets at the end of fiscal year *t* – 1. Past return is the stock return over the period from month *t* – 12 until *t* – 2. Whenever possible, our variable construction follows Fama and French (2015a, b). We Winsorize all variables at the 1% and 99% levels.

of decline firms is quite similar to the market capitalization of intro firms. When we use a different measure of firm size like total assets, we arrive at a similar conclusion. Hence, we note that there is a relation between life-cycle stage and firm size. The different market valuations are a reflection of profitability and (past) growth across life-cycle stages.

When we focus on the book-to-market ratio, we find that intro firms have the lowest ratio with 0.62. Growth and mature firms have book-to-market ratios of 0.68 and 0.75, respectively. Shakeout firms have a book-to-market ratio of 0.90. Hence, they have, on average the highest book-to-market ratios. Decline firms have book-to-market ratios of 0.74. We find, however, no particular relation between firm life cycle and the debt-to-equity ratio of firms.

We see large cross-sectional differences in profitability and investment growth of firms, as the life-cycle classification relies on cash flows from operating and investing activities. Intro firms have a profitability of –0.42 and an asset growth of 37%. These numbers support the previous notion that intro firms raise capital to grow their business while still suffering from low cost efficiency and economies of scale. Growth firms have a profitability of 0.28 and an asset growth of 35%. These numbers reflect that growth firms have positive cash flows from operations but still invest in growing their business. Mature firms show the highest profitability of 0.36 but an investment growth of only 4%. As previously noted, they have the highest cost efficiency and economies of scale. Investment activities of mature firms are rather focused on maintenance than growth. Shakeout firms have a profitability of 0.13 and a negative investment growth of –3%. Decline firms have the lowest profitability of –0.53 and a negative asset growth of –5%.

Focusing on past returns, we note that intro firms have negative returns over the period from month $t-12$ until $t-2$ while all other firms have positive returns. Intro firms have a past return of –3%, and growth firms have a past return of 10%. Mature firms have the largest past return of 16%. Last but not least, shakeout and decline firms have past returns of 14% and 6%, respectively.

INVESTMENT PERFORMANCE

In this section, we look at the performance of portfolios formed by life-cycle stage. We first look at the buy-and-hold return before we look at the risk-adjusted return and the factor exposure.

Buy-and-Hold Return

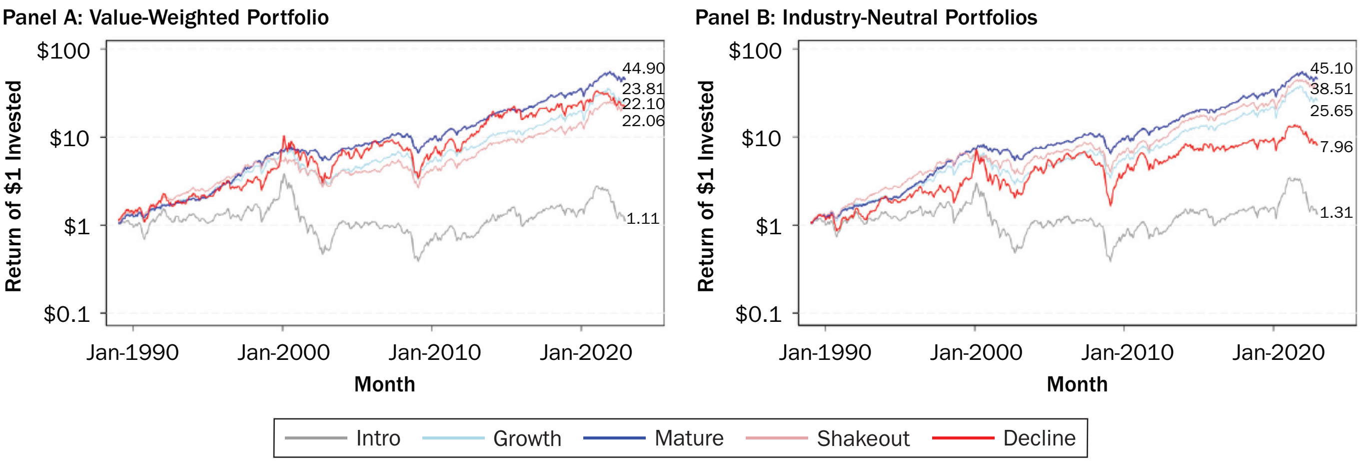
We build value-weighted portfolios by firm life cycle. We update the portfolios every month. We show the buy-and-hold returns of the portfolios in Panel A of Exhibit 5. One dollar that is invested in firms that are in the intro stage in January 1989 grows to only $1.11 in December 2022. The portfolio that invests in growth firms returns $23.81. The portfolio of mature firms performs best with a return of $44.90. The portfolios of shakeout and decline firms deliver almost the same performance with returns of $22.10 and $22.06, respectively.[3]

One concern of building value-weighted portfolios is that industries might be over- or underrepresented in certain life-cycle stages. Hence, the good performance

[3] In additional analyses, we look at the return of the portfolios during the bursting of the dot-com bubble (2000–2002) and the Global Financial Crisis (2007–2009). We find that mature firms performed better not only for the entire period but also in the subperiods of 2000–2002 and 2007–2009. Intro firms delivered the worst performance in each of the subperiods.

EXHIBIT 5

Buy-and-Hold Return by Firm Life Cycle



NOTES: This exhibit shows the cumulative buy-and-hold return of portfolios that invest in firms that are in a specific life-cycle stage. Panel A shows results for value-weighted portfolios. Panel B shows results for industry-neutral portfolios. All strategies start in January 1989 and end in December 2022.

of mature firms might be a result of a bet on industry performance. We address this issue by using industry-neutral portfolios. Our industry-neutral portfolios use industry weights that are calculated across our entire sample within each life-cycle portfolio. We use the Fama and French 10 industries to control for industry exposure. We show the buy-and-hold returns of the industry-neutral portfolios in Panel B of Exhibit 5. We note that the portfolio of intro firms still performs worst with a return of $1.31 in December 2022. The performance of the portfolio that invests in growth firms is almost unchanged. It returns $25.65 at the end of the holding period. The portfolio of mature firms still delivers the best performance with a return of $45.10. We note strong changes for the portfolios of shakeout and decline firms. While controlling for the industry exposure substantially improves the performance of shakeout firms ($38.51 vs. $22.10), the performance of decline firms is considerably worse ($22.06 vs. $7.96). We conclude that there are large cross-sectional differences in performance across life-cycle stages even after controlling for industry exposure.

In Exhibit 6, we calculate the annualized excess returns and standard deviations to gain more insights about the differences in buy-and-hold performance across life-cycle stages. Both annualized excess returns and standard deviations are calculated from monthly mean returns. We show the annualized versions of these variables to facilitate the calculation of Sharpe (1966) ratios. When focusing on the annualized excess return of the value-weighted portfolios in Panel A, we note that the portfolio investing in intro firms shows the lowest return of only 1.61% a year. At the same time, this portfolio shows the highest standard deviation of 27.76%. Consequently, the resulting Sharpe ratio of 0.07 is the lowest of all portfolios.

The remaining portfolios show returns that are quite similar in magnitude. Portfolios of growth and mature firms have average excess returns of 8.81% and 9.99% a year. While the portfolio of shakeout firms has an annualized return of 8.31%, the portfolio of decline firms actually has the highest annualized return of 10.77%.

The high return of decline firms, however, comes at a cost. The annualized standard deviation of the portfolio investing in decline firms is 27.70% and as high as for the portfolio investing in intro firms. The Sharpe ratio of 0.39 is the second lowest

EXHIBIT 6
Sharpe Ratios

	(1) Intro	(2) Growth	(3) Mature	(4) Shakeout	(5) Decline
Panel A: Value-Weighted Portfolios					
Excess Return, Annualized (%)	1.61	8.81	9.99	8.31	10.77
Standard Deviation, Annualized (%)	27.76	18.73	13.98	17.47	27.70
Sharpe Ratio	0.07	0.47	0.71	0.47	0.39
Panel B: Industry-Neutral Portfolios					
Return, Annualized (%)	2.07	8.99	10.05	10.14	7.64
Standard Deviation, Annualized (%)	27.64	18.46	14.28	17.72	28.12
Sharpe Ratio	0.07	0.49	0.70	0.57	0.27

NOTES: This exhibit shows the annualized excess return of portfolios that invest in firms that are in a specific life-cycle stage. The annualized excess returns and standard deviations are calculated from monthly mean returns. The Sharpe (1966) ratio is then the annualized excess return divided by the annualized standard deviation.

Sharpe ratio. The portfolios investing in growth and shakeout firms have very similar standard deviations of 18.73% and 17.47%, respectively. The Sharpe ratios are 0.47 for both portfolios.

The portfolio of mature firms has the lowest annualized standard deviation of only 13.98%. The Sharpe ratio of 0.71 is the highest of all portfolios. Comparing it with the other Sharpe ratios, investors of mature firms receive a higher compensation per unit of risk. The lower volatility of mature firms then also explains why this portfolio delivered a higher buy-and-hold return than the portfolio of decline firms while having lower annualized excess returns.[4]

The results for the industry-neutral portfolios in Panel B of Exhibit 6 are similar. The portfolio of mature firms still shows the highest Sharpe ratio, whereas the portfolio of intro firms shows the lowest Sharpe ratio. The summary statistics presented in Exhibit 6 do not allow us to draw any conclusions about the risk-adjusted performance. We turn to this issue in the next section.

Factor Exposure

We look at the risk-adjusted performance and at the factor exposure of firms by life cycle and employ the following time-series regression, that is,

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i MKTRF_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + u_i UMD_t + \epsilon_{i,t}, \qquad (1)$$

where $r_{i,t}$ denotes the value-weighted return of portfolio i at time t and $r_{f,t}$ denotes the return of the risk-free rate at time t; α_i is the constant and a measure of the abnormal performance; $MKTRF_t$ is the market excess return; SMB_t and HML_t are the Fama and French (1993) size and value factors; and RMW_t and CMA_t are the Fama and French (2015a, b) profitability and investment factors; UMD_t is the Carhart (1997) momentum factor. Lastly, $\epsilon_{i,t}$ is the error term with mean zero.

We show results in Exhibit 7. Only the portfolio that invests in intro firms shows a significant alpha. The alpha is –0.26% a month and significant at the 10% level (t-ratio: –1.93). We conclude that intro firms significantly underperformed. The other

[4] A portfolio with a one-year return of –50% needs a 100% return in the next year to deliver a buy-and-hold return of 0%. In this example, the annualized mean return is 25%. Hence, the arithmetic mean return is overstating the buy-and-hold return. Portfolios with high volatility have a higher likelihood of experiencing large negative returns.

EXHIBIT 7
Factor Exposure

	(1) Intro	(2) Growth	(3) Mature	(4) Shakeout	(5) Decline
Alpha	–0.26*	0.06	0.04	–0.12	0.28
	(–1.93)	(0.95)	(1.00)	(–1.12)	(1.59)
MKTRF	1.14***	1.09***	0.95***	1.07***	1.13***
	(33.62)	(67.79)	(100.56)	(39.66)	(25.68)
SMB	0.65***	0.08***	–0.05***	–0.00	0.79***
	(13.38)	(3.66)	(–3.41)	(–0.05)	(12.54)
HML	–0.38***	–0.11***	–0.11***	–0.13***	–0.47***
	(–6.53)	(–4.08)	(–6.44)	(–2.77)	(–6.20)
RMW	–0.75***	–0.09***	0.22***	0.05	–0.75***
	(–12.39)	(–2.95)	(13.05)	(1.10)	(–9.52)
CMA	–0.39***	–0.24***	0.18***	0.29***	0.28**
	(–4.60)	(–5.95)	(7.45)	(4.27)	(2.53)
UMD	–0.03	–0.02	–0.02*	–0.05**	–0.02
	(–0.94)	(–1.42)	(–1.89)	(–2.00)	(–0.44)
R^2	0.898	0.949	0.969	0.836	0.826
Adjusted R^2	0.896	0.949	0.968	0.834	0.824
Observations	408	408	408	408	408

NOTES: This exhibit shows factor loadings of value-weighted portfolios that invest in firms that are in a specific life-cycle stage. We regress the monthly excess returns on a Fama and French (2015a, b) five-factor model augmented by the Carhart (1997) momentum factor. The constant (alpha) is multiplied by 100 and expressed in percentage. MKTRF is the market excess return. SMB and HML are the Fama and French (1993) size and value factors, and RMW and CMA are the Fama and French (2015a, b) profitability and investment factors. UMD is the Carhart (1997) momentum factor.

firms neither outperformed nor underperformed the market. Hence, the good performance of mature firms is only a compensation for systematic risk.

Focusing on the factor sensitivities, we note that intro and decline firms show the highest exposure to the market factor (betas of 1.14 and 1.13, respectively). The portfolio of mature firms is less volatile than the market with a beta of 0.95. This finding supports the evidence presented in the last section that mature firms tend to be less risky than intro and decline firms.

Consistent with the summary statistics that we showed in Exhibit 4, intro and decline firms are rather small firms and, consequently, have a strong exposure to the size factor (betas of 0.65 and 0.79, respectively). Growth firms have a small exposure to the size factor as well (beta of 0.08). Mature firms hedge against the size factor (beta of –0.05), while the exposure of shakeout firms is not significant. All portfolios show a negative exposure to the value factor; that is, all portfolios seem to hedge against the value factor.

The exposure to the profitability factor reflects information from cash flows that we used for the life-cycle classification and is in line with the summary statistics in Exhibit 4. Intro and decline firms have negative cash flows from operating activities and have a negative exposure to the profitability factor (betas of –0.75 each). Growth firms have a slightly negative exposure to the profitability factor as well (beta of –0.09). Mature firms, by contrast, have a positive exposure (beta of 0.22). The portfolio of shakeout firms has no significant exposure.

Turning to the investment factor, we note that intro and growth firms that have negative cash flows from investing activities and that show the highest asset growth have a strong negative exposure to the investment factor (betas of –0.39 and –0.24, respectively).[5] Mature, shakeout, and decline firms have positive exposures (betas of 0.18, 0.29, and 0.28, respectively).

Finally, none of the portfolios reveals a positive exposure to the momentum factor. The portfolios containing mature and shakeout firms show negative exposures (betas of –0.02 and –0.05, respectively) while the other portfolios show no significant exposure.[6]

Overall, we conclude that the good performance of mature firms is not due to alpha but rather a compensation for exposure to the profitability and investment factors. At the same time, however, a portfolio of mature firms seems to carry less systematic risk than the market and hedges against size and value risk. Last but not least, we want to point out that the R^2 and the adjusted R^2 are highest for the portfolio of mature firms. The factor model has sharply different explanatory power for firms in different life-cycle stages, supporting our assertion that firm life cycles might help us to understand asset prices better.

RISK PREMIUMS

We showed that the factor exposure is different for firms in different life-cycle stages in the previous section. Now, we turn to the question whether firms in different life-cycle stages also realize different risk premiums. Estimating risk premiums over the entire firm universe assumes that all firms in the economy exhibit the same risk premiums. However, the risk premiums might be different for subsamples of firms. To test our hypothesis that risk premiums might be different across life-cycle stages, we run cross-sectional Fama and MacBeth (1973) regressions on the firm level. In the spirit of Brennan, Chordia, and Subrahmanyam (1998), we run the following regression:

$$r_{i,t} - r_{f,t} = \gamma_{0,t} + \gamma_{1,t} X_{i,t-1} + \epsilon_{i,t}, \tag{2}$$

where $r_{i,t}$ denotes the return of stock i at time t and $r_{f,t}$ denotes the return of the risk-free rate at time t; $X_{i,t-1}$ is a vector of firm characteristics that are known to correlate with stock returns. We include beta, size, book-to-market ratio, operating profitability, investment, and past return (Fama and French 1993, 2015a, b, 2018; Carhart 1997).

Instead of using unadjusted firm characteristics, we use z-scores. We truncate all z-scores at values of –3 and +3. We normalize on a monthly basis to not introduce look-ahead bias. If any of the firm characteristics is positively associated with returns, we expect a positive and significant risk premium (γ). In a first step, we estimate Equation (2) for the entire universe of firms in our sample. We calculate z-scores by subtracting the cross-sectional mean of *all firms* in our sample and dividing by standard deviation. Next, we estimate Equation (2) for all firms within a specific life-cycle stage. We calculate z-scores by subtracting the cross-sectional mean of firms in the *same life-cycle stage* and dividing by standard deviation.

We show results in Exhibit 8. All coefficients are multiplied by 100 and expressed in percentages. We first show factor premiums for the entire sample in column (1). We find no significant relation between excess returns and beta. This is consistent with previous work that has documented the low-beta anomaly (Black, Jensen,

[5] Firms that invest conservatively tend to outperform firms that invest aggressively. Hence, firms with high asset growth tend to have negative exposure to the investment factor.

[6] We get very similar factor exposures when we include industry returns (in excess of the market return) as additional explanatory variables in the regression.

EXHIBIT 8

Fama and MacBeth (1973) Regressions

	(1) All	(2) Intro	(3) Growth	(4) Mature	(5) Shakeout	(6) Decline	(7) F-Test
Beta	0.08	0.12	0.14	0.11	0.06	0.22*	0.32
	(0.79)	(1.07)	(1.41)	(1.36)	(0.49)	(1.74)	
Size	–0.40***	–0.77***	–0.24***	–0.35***	–0.57***	–0.82***	4.36***
	(–3.88)	(–5.56)	(–2.92)	(–4.44)	(–4.85)	(–4.91)	
BTM	0.23***	0.35***	0.11	0.11*	0.23*	0.51***	2.27*
	(3.48)	(3.09)	(1.42)	(1.72)	(1.82)	(3.26)	
Profitability	0.11***	0.08	–0.01	0.09***	0.17**	0.07	1.23
	(3.43)	(1.45)	(–0.30)	(2.76)	(2.22)	(0.96)	
Investment	–0.31***	–0.24***	–0.22***	–0.11***	–0.14	–0.45***	3.80***
	(–8.56)	(–4.71)	(–5.59)	(–3.18)	(–1.64)	(–4.43)	
Past Return	0.19**	0.23**	0.32***	0.13	0.16	0.09	0.64
	(2.11)	(2.04)	(3.30)	(1.64)	(1.15)	(0.69)	
Constant	1.05***	0.71	0.90***	1.19***	1.34***	1.34***	
	(3.30)	(1.64)	(2.90)	(4.50)	(4.27)	(2.83)	
R^2	0.033	0.036	0.049	0.042	0.059	0.054	
Observations	1,353,913	245,035	384,474	505,253	119,631	99,520	

NOTES: This exhibit shows factor risk premiums across life-cycle stages. We use cross-sectional Fama and MacBeth (1973) regressions in the spirit of Brennan, Chordia, and Subrahmanyam (1998; firm-level regressions) to estimate risk premiums. We regress monthly excess returns on a set of firm characteristics. Our firm characteristics include beta, firm size, book-to-market ratio, profitability, investment, and past return. These factors have been shown to be correlated with future returns by previous research (Fama and French 1993, 2015a, b; Carhart 1997). We normalize firm characteristics on a monthly basis. In the first column, we normalize by subtracting the cross-sectional mean of all firms in our sample and dividing by standard deviation. In all other columns, we normalize by subtracting the cross-sectional mean of firms in the same life-cycle stage and dividing by standard deviation. We truncate the z-scores at values of –3 and +3. All coefficients are multiplied by hundred and expressed in percentages. The last column shows an F-test used to test the coefficient estimates of intro, growth, mature, shakeout, and decline firms for joint differences. *t*-Statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and Scholes 1972; Frazzini and Pedersen 2014). The coefficients for firm size and book-to-market ratio have the expected signs. While large firms have lower returns than small firms, firms with high book-to-market ratios have higher returns than firms with low book-to-market ratios. In particular, a one-standard-deviation increase in size (book-to-market ratio) is associated with a 0.40% (0.23%) decrease (increase) in monthly return. Both coefficient estimates are significant at the 1% level (*t*-ratios of –3.88 and 3.48, respectively). This is in line with the evidence provided in Fama and French (1993). Further, we find a positive coefficient for profitability and a negative coefficient for investment. A one-standard-deviation increase in the profitability (investment) of a firm is associated with a 0.11% (0.31%) increase (decrease) in monthly return. The coefficients are both significant at the 1% level (*t*-ratios of 3.43 and –8.56, respectively). Again, the sign of the coefficients is consistent with previous work (Fama and French 2015a, b). Last but not least, we find that a one-standard-deviation increase in the past return is associated with a 0.19% increase in monthly return. The coefficient is significant at the 5% level (*t*-ratio of 2.11).

We look at whether there exists cross-sectional variation in the magnitude of risk premiums across life-cycle stages. We start by focusing on firm size. While the size premium is significant at the 1% level for each life-cycle stage, it is considerably larger for intro, shakeout, and decline firms (–0.77%, –0.57%, and –0.82%, respectively) than for growth and mature firms (–0.24% and –0.35%, respectively). When we conduct an

F-test to test for joint equality of the risk premiums, the null hypothesis of no significant differences across life-cycle stages is rejected at the 1% significance level.

We make a similar observation when analyzing the value factor. The value premium is largest for intro and decline firms (0.35% and 0.51%, respectively). In addition, it is significant at the 1% level only for these subsamples. Growth firms do not realize a significant value premium at all. Mature and shakeout firms realize comparatively small risk premiums (0.11% and 0.23%, respectively) that are significant at the 10% level. Again, the *F*-test suggests that the differences in the value premium across life-cycle stages is significant. The finding that the value premium is largest for decline firms aligns with Dickinson, Kassa, and Schaberl (2018), who find that accounting information is more important for decline firms than for growth and mature firms. The finding that the size and value premiums are largest for intro and decline firms also supports the notion that these risk premiums compensate for the risk of corporate failure.

The risk premium for firm profitability is only significant for the subsample of mature and shakeout firms. The coefficient is 0.09% for mature firms, and it is 0.17% for shakeout firms. The coefficient estimates are significant at the 1% and 5% levels, respectively. It seems that the profitability factor derives its significance from firms that have stable business models. However, we want to point out that the F-test is not significant; that is, we cannot reject the null hypothesis of equality of coefficient estimates.

Focusing on the investment factor, we note that the risk premiums are most pronounced for intro, growth, and decline firms. The risk premiums amount to –0.24%, –0.22%, and –0.45%, respectively. The coefficient estimates for these subsamples of firms are significant at the 1% level. The risk premium is also significant for mature firms. However, the coefficient is considerably smaller (–0.11%). Shakeout firms show no significant risk premium for investment. The *F*-test suggests that the differences in the investment premium across life-cycle stages are significant at the 1% level.

While we find no significant risk premium related to past returns for mature, shakeout, and decline firms, intro and growth firms show a significant risk premium. Intro firms have a risk premium of 0.23% a month that is significant at the 5% level, and growth firms have a risk premium of 0.32% a month that is significant at the 1% level. The finding that growth firms have the largest risk premium regarding the momentum factor is in line with conventional wisdom, as the terms “growth” and “momentum” are often used interchangeably. The *F*-test, however, cannot confirm that these differences are significant.

The finding that the risk premiums are different across life-cycle stages has important implications for investors. A strategy that builds upon exploiting the different factors might work best when focusing on certain subsets of firms but not (necessarily) unconditionally.

In an effort to show that risk premiums might be exploited more efficiently by incorporating life-cycle information, we use the risk premiums to calculate the expected return of a stock. In particular, we compare an unconditional strategy with a strategy that estimates risk premiums conditional on firm life cycle, that is, we use the risk premiums shown in Exhibit 8 to calculate expected returns and sort stocks into quintiles based on expected returns. We construct a value-weighted long–short portfolio that invests in stocks with high expected returns and shorts stocks with low expected returns. We use NYSE breakpoints for the sort to make sure that our results are not driven by firm size.

We show results in Exhibit 9. In Panel A, we use risk premiums estimated over the entire sample period. We first focus on the unconditional strategy that does not incorporate life-cycle information in the estimation of factor premiums. The portfolio that contains the stocks with the lowest expected returns generates a monthly

EXHIBIT 9
Expected Return Sorts

	Low	2	3	4	High	HML	*t*-Statistic
Panel A: Full Sample							
Unconditional	0.67	0.93	0.95	0.90	1.16	0.49*	1.96
Conditional	0.64	0.79	0.96	1.15	1.36	0.72***	2.80
Difference						–0.23*	
t-Statistic						–1.92	
Panel B: Expanding Window							
Unconditional	0.65	0.95	0.91	0.93	1.11	0.46*	1.77
Conditional	0.61	0.75	0.86	0.94	1.40	0.79***	2.77
Difference						–0.32**	
t-Statistic						–2.00	

NOTES: This exhibit shows monthly excess returns for portfolios formed based on expected returns. We use monthly cross-sectional Fama and MacBeth (1973) regressions at the firm level to estimate risk premiums. We estimate risk premiums unconditionally using the entire sample and conditional on firm life cycle. We use the risk premiums to calculate the expected returns of the stocks in our sample. We sort stocks into quintile portfolios based on their expected return. Our portfolio sorts use NYSE breakpoints. The first portfolio contains the stocks with the lowest expected returns, and the last portfolio contains stocks with the highest expected return. HML (high-minus-low) is a long–short portfolio that invests in stocks with high expected returns and shorts stocks with low expected returns. All returns are value weighted. Panel A uses risk premiums estimated in monthly cross-sectional regressions over the full sample (“look-ahead bias”), whereas Panel B uses risk premiums estimated in monthly cross-sectional regressions with an expanding window (“point in time”). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

excess return of 0.67%. By contrast, the portfolio that contains the stocks with the highest expected returns generates a monthly excess return of 1.16%. The long–short portfolio consequently has a return of 0.49% that is significantly different from zero at the 10% level.

Focusing on the strategy that uses risk premiums estimated conditional on firm life cycle, we note that the return spread of the high- and low-expected return portfolios is even larger. The portfolio that contains the stocks with the lowest expected returns generates a monthly excess return of 0.64%. This estimate is slightly lower than the estimate for the unconditional strategy. The portfolio that contains the stocks with the highest expected returns generates a monthly excess return of 1.36%. Comparing it with the portfolio return of the unconditional strategy, we note that the return is higher. The long–short strategy delivers a monthly excess return of 0.72% a month. The return is significantly different from zero at the 1% level.

We further note that the difference in the returns of the long–short portfolios is also statistically significant. The difference amounts to 0.23% and is significantly different from zero at the 10% level. The performance difference can be partly attributed to the fact that the conditional strategy assigns a higher (lower) weight to mature (intro) firms in the long portfolio than the unconditional strategy. Similarly, the conditional strategy assigns a lower (higher) weight to mature (intro) firms in the short portfolio than the unconditional strategy.

One shortcoming of the analysis shown in Panel A of Exhibit 9 is that we use the entire sample to estimate risk premiums. In other words, the analysis in Panel A uses information that is not available in real time and suffers from look-ahead bias. To address this issue, we also estimate risk premiums using expanding windows. For each month t, we estimate risk premiums in monthly cross-sectional regressions from the first month of our sample until month $t - 1$. The risk premiums in month t are then the time-series averages of risk premiums from the first month until month $t - 1$. We show results in Panel B of this exhibit.

The unconditional long–short strategy now delivers a monthly return of 0.46%. The estimate is slightly lower than in the previous analysis. The return, however, is still significantly different from zero at the 10% level. Turning to the strategy that estimates risk premiums conditional on firm life cycle, we note that the return of the long–short portfolio is now 0.79% a month and that the return still is statistically significant at the 1% level. The return is now even higher than in the previous analysis. The return difference between the two strategies amounts to 0.32% and is statistically significant at the 5% level. The results in Panel B of Exhibit 9 corroborate our previous findings. We conclude that conditioning risk premiums on firm life cycle might help to harvest risk premiums.

CONCLUSION

Overall, we find that there exist large differences across life-cycle stages. Investors holding mature firms realize higher buy-and-hold returns. At the same time, portfolios of mature firms show the least volatility. We find that the good performance of mature firms is driven by exposure to the profitability and investment factors.

Additionally, we analyze factor risk premiums. We find that factor risk premiums are different across life-cycle stages. The size and value risk premiums are largest for intro and decline firms, whereas the profitability risk premium is solely driven by mature firms and the momentum risk premium is solely driven by growth firms. Hence, our findings have important implications for investors that want to harvest factor risk premiums.

Future research might explore other dimensions of firm life cycle and factor investing. For instance, our contextual modeling approach could be extended to account for the impact of economic conditions.

ENDNOTE

The views and opinions expressed are those of the authors and do not necessarily reflect the views of Quoniam Asset Management GmbH, its affiliates, or its employees; do not constitute an offer or solicitation of an offer, or any advice or recommendation, to purchase any securities or other financial instruments; and may not be construed as such. Quoniam Asset Management GmbH commercially operates in the field of factor investing. We thank Stephen Penman, Scott Murray, Jannis Bischof, Brian Payne, Gordon Karels, Frederik Horn, Thomas Johann, Stefan Scharnowski, Oliver Spalt, John Geppert, and Erik Theissen as well as seminar participants at the University of Mannheim and Quoniam Asset Management for helpful comments. Last but not least, we thank conference participants at the 4th Frontiers of Factor Investing Conference in Lancaster, England, and conference participants at the 2024 FMA annual meeting in Grapevine, Texas.

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