Firm Life Cycle and the Cross-section of Stock Returns

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Abstract

The firm life cycle matters for asset pricing. We find that mature firms, i.e. firms with positive cash flows from operating activities and negative cash flows from investing and financing activities, have historically delivered the best buy-and-hold performance for investors in our sample of US stocks. Additionally, 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 driven by mature and shake-out firms. The momentum risk premium originates in intro and growth firms. Our findings have important implications for factor investing. Conditioning factor strategies on firm life cycle has the potential to improve the efficacy to harvest risk premiums.

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1 Introduction

The firm life cycle concept serves as a foundational framework for understanding the transformation of companies over time. From their inception to maturity and, possibly, decline, firms undergo structural changes that fundamentally reshape their strategies and risk-taking behavior (Quinn and Cameron, 1983; Miller and Friesen, 1984). Despite the substantial body of work investigating the ramifications of firm life cycle stages on various aspects of corporate finance, there remains a gap in understanding how the concept of firm life cycle matters for asset pricing. This research aims to bridge this gap by examining how the Fama and French (2015a,b) five-factor model aligns with the distinct stages of a firm's life cycle.

Using a sample of 13,534 distinct US firms from 1989 until 2022, our results provide interesting insights into the interplay between a firm's life cycle stages and factor models in unraveling the complexities of corporate behavior, risk profiles, and investment strategies. One of our key findings centers on the discernible differences in performance and volatility among firms at various life cycle stages. Specifically, investors holding mature firms stand to gain higher buy-and-hold returns, accompanied by the least volatility in their portfolios. This phenomenon underscores the heightened stability and performance of firms as they reach maturity. Importantly, 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.

In addition to dissecting the performance and volatility dynamics, our study analyzes 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 shake-out 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.

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 financial factors and the dynamic evolution of firms. The 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.

Empirical studies have shown that accounting information must be interpreted through the lens of a firm's life cycle stage (Anthony and Ramesh, 1992; Hribar and Yehuda, 2015). This suggests that as firms transition between life cycle phases, their financial statements provide differing insights into their underlying economic conditions and future prospects. Given the pivotal role of a firm's life cycle phase in shaping its profitability outlook, it follows that such stages also impact the valuation of the firms' underlying cash flows and accruals (Cantrell and Dickinson, 2020; Vorst and Yohn, 2018; Dickinson, 2011; Hribar and Yehuda, 2015).

Recent research by Dickinson et al. (2018) highlights the evolving nature of investor preferences regarding accounting measures, shifting from traditional metrics to analyst forecasts based on a firm's life cycle stage. Moreover, firms adjust their disclosure practices and operational strategies in accordance with their position in the life cycle (Chen et al., 2002; Cohen et al., 2009). This underscores the pervasive influence of the life cycle on multiple dimensions of a firm's financial behavior.

Studies such as Agarwal and Gort (2002) underscore the pivotal role of firm survival rates in relation to their life cycle stages. Pastor and Veronesi (2003) further contributed to this discourse by highlighting the heightened risk associated with young firms, characterized by elevated idiosyncratic return volatility due to uncertainty surrounding profitability. This volatility diminishes over time as investors gain insights into the firm's operations, indicating a potential link between risk, life cycle stage, and the firm's information environment.

The remainder of this study is structured as follows. We describe data and methodology in Section 2. We discuss our main results in Section 3. We examine risk premiums in Section 4. We conclude in Section 5.

2 Data & Methodology

In this section, we give an overview of our sample. In Section 2.1, we describe the data, and in Section 2.2, we describe the life cycle classification.

2.1 Data

We use firm-level data from two sources. We download US 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). We replace missing prices with the bid-ask average. Whenever a stock is delisted, we replace the return by the delisting return. Last but not least, we drop public utilities and financial firms (two-digit sic code: 49 and 60-67, respectively).

We merge stock return data with accounting information from the CRSP/Compustat Merged annual database to run cross-sectional Fama and MacBeth (1973) regressions in the latter part of our 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).

For the Fama and MacBeth (1973) regressions we 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 website (value-weighted return of all NYSE, AMEX, and NASDAQ stocks) as our market index. 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 by 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 by 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. We winsorize these variables at the 1% and 99% levels. Our sample spans the period from 1989 until 2022. In total, we have data on 13,534 distinct firms.

2.2 Firm Life Cycle

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. The approach of Dickinson (2011) is summarized in Table 1. We describe the classification of Dickinson (2011) in more detail below.

[Table 1 over here.]

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, loose money and try to grow their business. Further, firms in an introductory stage rely on financing from investors and creditors.

By contrast to firms in the introductory stage, firms in the growth stage have positive cash flows from operations. They have, on average, well-functioning business models that allow these firms to be profitable. Just like firms in the introductory stage, they collect money from investors and creditors to further invest in their business models.

Firms in a mature stage have, just like firms in the growth stage, positive cash flows from operating activities and negative cash flows from investing activities. However, companies in the mature stage have negative cash flows from financing activities. These firms do no longer rely on money from investors and creditors but rather pay dividends, repurchase stocks, or pay back bonds and loans.

Firms in a shake-out 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 negative cash flows from financing activities. Hence, firms that are in a mature stage might turn into a firm that is in a shake-out stage, e.g., by a divestiture.

Last but not least, 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. Hence, both cash flow profiles share that decline firms are loosing money from their business model and rather divest their assets.

We argue that life cycle information can help to improve factor models explaining stock returns. Vorst and Yohn (2018) document that forecast accuracy of profitability and growth forecasts can be improved by incorporating life cycle information. In addition, Dickinson et al. (2018) show that accounting information is more important for investors of intro and decline firms whereas earnings forecasts are more important for investors of growth and mature firms in terms of equity market values. We make a similar prediction for asset pricing models and argue that cash flow information matters for asset pricing. A company that looses money from operations might not only have higher systematic risk but also established factor models might be less suited to explain the returns of the underlying stocks.

3 Results

This section is divided into two parts. First, we provide descriptive statistics by life cycle stage (Section 3.1). Second, we look at the investment performance and the factor exposure by life cycle stage (Section 3.2).

3.1 Descriptive Statistics

In a first step, we want to provide more hands-on information. We start by presenting examples for firms in different life cycle stages in Table 2. We highlight the three largest firms in each life cycle stage as of December 2022. Our examples consist of Uber Technologies, Alnylam Pharmaceuticals, and Coupang (intro), Amazon, Nvidia, and Merck & Co (growth), Apple, Microsoft, and Alphabet (mature), Berkshire Hathaway, Amgen, and General Electric (shake-out), and Boeing, Seagen, and Inspire Medical Systems (decline).

[Table 2 over here.]

In addition, to highlight that there is within-firm variation in life cycle over time, we plot the life cycle stages of Apple and Microsoft from 1989 until 2022 in Figure 1. Not only do both firms change their life cycle stage frequently, but they also change life cycle stages non-linearly. For instance, in the 1990s, Microsoft repeatedly switched back and forth between the growth and the mature stages. Likewise, in the 2010s, Apple switched back and forth between the growth and shake-out stages. Again, we argue that the changes in life cycle stages contain important information and reflect managerial decisions like changes in leverage or divestitures.

[Figure 1 over here.]

We also look at variation in life cycle stages over the business cycle. In Figure 2, we plot the fraction of firms within a specific life cycle stage. We note that intro, growth, mature, shake-out, 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%.

[Figure 2 over here.]

Next, to highlight differences in firm characteristics, we show summary statistics at the firm level in Table 3. We note that intro firms have, on average, a market capitalization of 0.44 billion USD. Growth firms are considerably larger with an average market capitalization of 2.43 billion USD. Mature firms have, on average, the largest market capitalization. The average market capitalization for mature firms is 4.65 billion USD. Shake-out firms have, on average, a market capitalization that is quite similar to the market capitalization of growth firms. Likewise, the market capitalization of decline firms is quite similar to the market capitalization of intro firms. Hence, we note that there is a relation between life cycle stage and firm size. When we use a different measure of size like total assets we arrive at a similar conclusion.

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. Shake-out 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 that have negative cash flows from operating and investing activities have a profitability of -0.42 and an asset growth of 37%. 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 into growing their business. Mature firms show the highest profitability of 0.36 but an investment growth of only 4%. Shake-out 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%.

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, shake-out and decline firms have past returns of 14% and 6%, respectively.

We argue that the cross-sectional differences in size, profitability, investment, and past return will lead to differences in return and factor exposures. We turn to this issue in the next chapter.

[Table 3 over here.]

3.2 Investment Performance

In this section, we look at the performance of value-weighted portfolios formed by life cycle stage. We first look at the buy-and-hold return in Section 3.2.1 before we look at the risk-adjusted return and the factor exposure in Section 3.2.2. Last but not least, we briefly analyze the portfolio turnover in Section 3.2.3.

3.2.1 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 Figure 3. One dollar that is invested into firms that are in the intro stage in January 1989 grows to only $1.11 in December 2022. The portfolio that invests into growth firms returns $23.81. The portfolio of mature firms performs best. It would have returned $44.90. The portfolios of shake-out and decline firms deliver almost the same performance. An investment would have returned $22.10 and $22.06, respectively.

[Figure 3 over here.]

In Figure 4, we look at the performance of portfolios during subperiods. In particular, we look at the return during the bursting of the dotcom bubble (2000-2002), the financial crisis (2007-2009), and the Corona pandemic (2020-2022). We find that mature firms performed better not only about the entire period but also in the subperiods from 2000-2002 (Panel A) and 2007-2009 (Panel B). Over the period from 2020-2022, shake-out firms performed slightly better than mature firms. Intro firms delivered the worst performance in each of the subperiods.

[Figure 4 over here.]

In Table 4, 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, we note that the portfolio investing into intro firms shows the lowest return of only 1.61% per 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 excess returns of 8.81% and 9.99% per year on average. While a portfolio of shake-out firms has an annualized return of 8.31%, a 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 a portfolio investing into decline firms is 27.70% and as high as for the portfolio investing into intro firms. The Sharpe ratio of 0.39 is the second lowest Sharpe ratio. The portfolios investing into growth and shake-out 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.[1] The summary statistics presented in Table 4 do not allow, however, to draw any conclusions about the risk-adjusted performance. We turn

[1] 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.

to this issue in the next chapter.

3.2.2 Factor Exposure

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

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

where $r_{i,t}$ denotes the value-weighted return of portfolio i at time t and $r_{f,t}$ denotes the return of the riskfree 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 Table 5. Only the portfolio that invests into intro firms shows a significant alpha. The alpha is -0.26% per month and significant at the 10% level (t-ratio: -1.93). The other firms did neither outperform nor underperform 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 Table 3, 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 shake-out firms is not significant. All portfolios show a negative exposure to the value factor, i.e. all portfolios seem to hedge against the value factor.

The exposure to the profitability reflects the cash flow information that we used for the life cycle classification and is in line with the summary statistics in Table 3. 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 slight 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 shake-out 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).[2] Mature, shake-out, 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 shake-out firms show negative exposures (betas of -0.02 and -0.05, respectively) while the other portfolios show no significant exposure.

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

[2] Firms that invest conservatively tend to outperform firms that invest aggressively.

stages supporting our assertion that firm life cycles might help understand asset prices better.

[Table 5 over here.]

3.2.3 Portfolio Turnover

We look at the frequency with which firms change their life cycle stage to gain insights into the turnover of our portfolios. We show transition probabilities for the firms in our sample in Table 6. The diagonal in Panel A shows the probabilities that firms stay in the same life cycle stage in the next year. Intro firms have a probability of 50.89% to remain intro firms. The probability for growth firms to remain in the same life cycle stage is slightly lower with 48.38%. Mature firms, by contrast, have a relatively high probability of 61.38% to remain mature. Then again, shake-out firms have a surprisingly low probability of 23.92% to remain in the same life cycle. Interestingly, shake-out firms are most likely to become mature firms in the next year. Last but not least, decline firms have a probability of 40.16% to remain in the same life cycle stage.

The turnover of an equally-weighted portfolio is then one minus the probability to stay in the same life cycle stage. In other words, for a portfolio that invests into intro firms, 49.11% of stocks are turned over on a year-by-year basis. The corresponding turnover for a portfolio that invests into growth stocks is 51.62%. A portfolio that invests into mature firms would show an annual turnover of only 38.62% whereas portfolios investing into shake-out and decline firms would show a turnover of 76.08% and 59.84%, respectively.

We also highlight in Panel B the probabilities for firms in each life cycle stage being delisted. Not surprisingly, intro and decline firms have the highest probabilities of being liquidated or being dropped from the exchange due to poor performance. We conclude that the investment in mature firms is associated with the least amount of portfolio turnover.

[Table 6 over here.]

4 Risk Premiums

We show that the factor exposure is different for firms in different firm 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 if there exist large cross-sectional differences in firms. To test our hypothesis that risk premiums might be different for firms over the life cycle, we run cross-sectional Fama and MacBeth (1973) regressions on the firm level. In the spirit of Brennan et al. (1998), we run the following regression, i.e.

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

where $r_{i,t}$ denotes the return of stock i at time t and $r_{f,t}$ denotes the return of the riskfree 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; Carhart, 1997).

Instead of using unadjusted firm characteristics, we use z-scores. 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 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).

We show results in Table 7. All coefficients are multiplied by hundred and expressed in percentage. 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 et al., 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, shake-out, and decline firms (-0.77%, -0.57%, and -0.82%, respectively) than for growth and mature firms (-0.24% and -0.35%, respectively). 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 shake-out firms realize comparatively small risk premiums (0.11% and 0.23%, respectively) that are significant at the 10% level. The finding that the value premium is largest for decline firms aligns with Dickinson et al. (2018) who find that accounting information are 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 shake-out firms. The coefficient is 0.09% for mature firms, and it is 0.17% for shake-out 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.

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 is significant at the 1% level. The risk premium is also significant for mature firms. However, the coefficient is considerably smaller (-0.11%). Shake-out firms show no significant risk premium for investment.

While we find no significant risk premium related to past returns for mature, shake-out, and decline firms, intro and growth firms show a significant risk premium. Intro firms have a risk premium of 0.23% per month that is significant at the 5% level, and growth firms have a risk premium of 0.32% per 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 finding that the risk premiums are different across life cycle stages has important implications for investors. A strategy that builds upon exploiting the value, profitability, and momentum factors might work best when focusing on certain subsets of firms but not (necessarily) unconditionally.

[Table 7 over here.]

In an effort to show that risk premiums might be exploited more efficiently by incorporating life cycle information, we use the risk premiums to measure 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, i.e. we use the risk premiums shown in Table 7 to calculate expected returns and sort stocks into quintiles based on expected returns. We construct a value-weighted long-short portfolio that invests into stocks with high expected returns and shorts stocks with low expected return. We use NYSE breakpoints for the sort to make sure that our results are not driven by firm size.

We show results in Table 8. 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 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% per 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.

[Table 8 over here.]

One shortcoming of the analysis shown in Panel A 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. We show results in Panel B.

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% per 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 corroborate our previous findings. We conclude that conditioning risk premiums on firm life cycle might help to harvest risk premiums.

In a last step, we look at differences across life cycle stages. We repeat the analysis conducted in Table 8 Panel B, and we use the same breakpoints for the expected return portfolios. However, we show results for life cycle stages separately. Hence, this analysis allows us to identify where the improvement in performance of the conditional model stems from.

We show results in Table 9. Panels A, B, C, D, and E show results for intro, growth, mature, shake-out, and decline firms, respectively. We find significant differences between the unconditional model and the conditional model only for the subset of stocks that are in a growth stage (Panel B). The long-short strategy of the unconditional model delivers a monthly return of 0.49% whereas the conditional model delivers a monthly return of 1.21%. The difference amounts to 0.72% and is statistically significant at the 5% level. For all other life cycle stages, we find no significant differences between the unconditional model and the conditional model. Hence, the better performance of the conditional model stems not from selection of firms within life cycle stage but rather from allocation, i.e. assigning larger weights to, e.g., mature firms.

[Table 9 over here.]

5 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.

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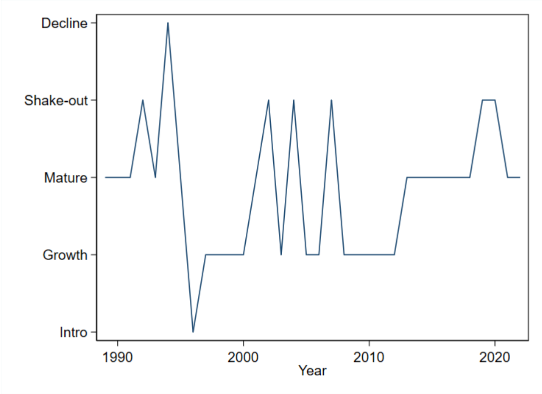
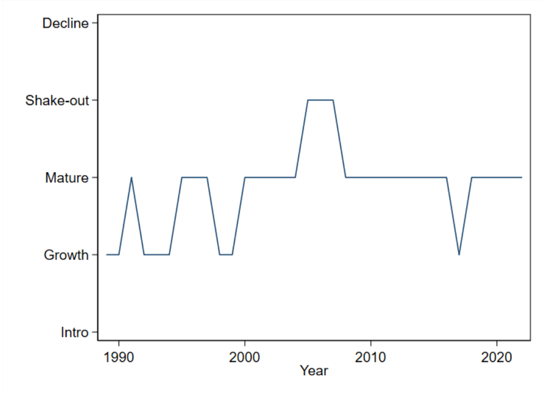
A Appendix - Figures and Tables



(a) Apple



(b) Microsoft

Figure 1: Apple's and Microsoft's Life Cycle Stages
These figures show the life cycle stages of Apple and Microsoft from 1989 until 2022. The x-axis denotes the year and the y-axis denotes the life cycle stage. The classification of life cycle stages follows Dickinson (2011).

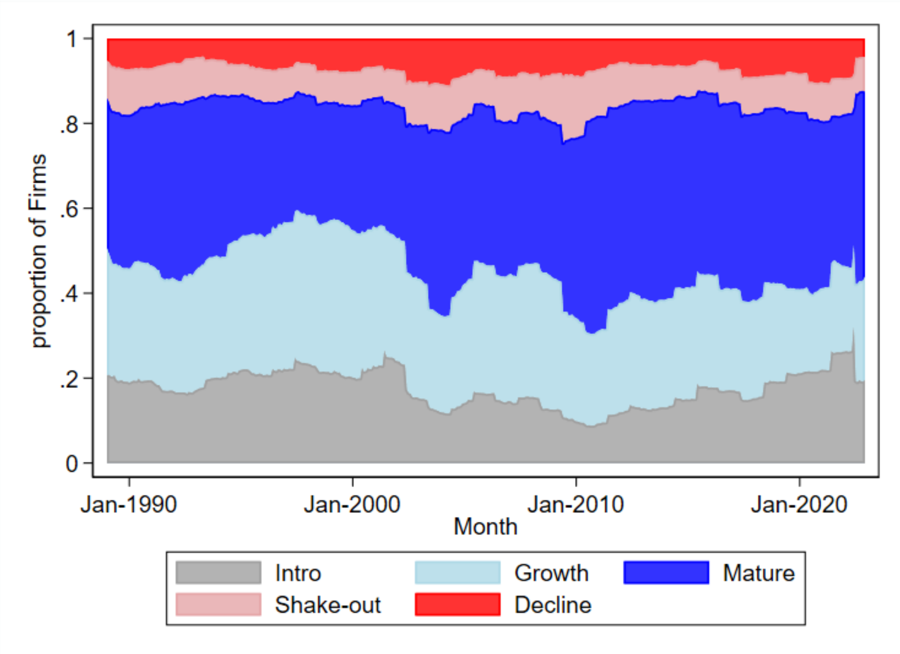


Figure 2: Life Cycle Stages over Time

This figure 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.

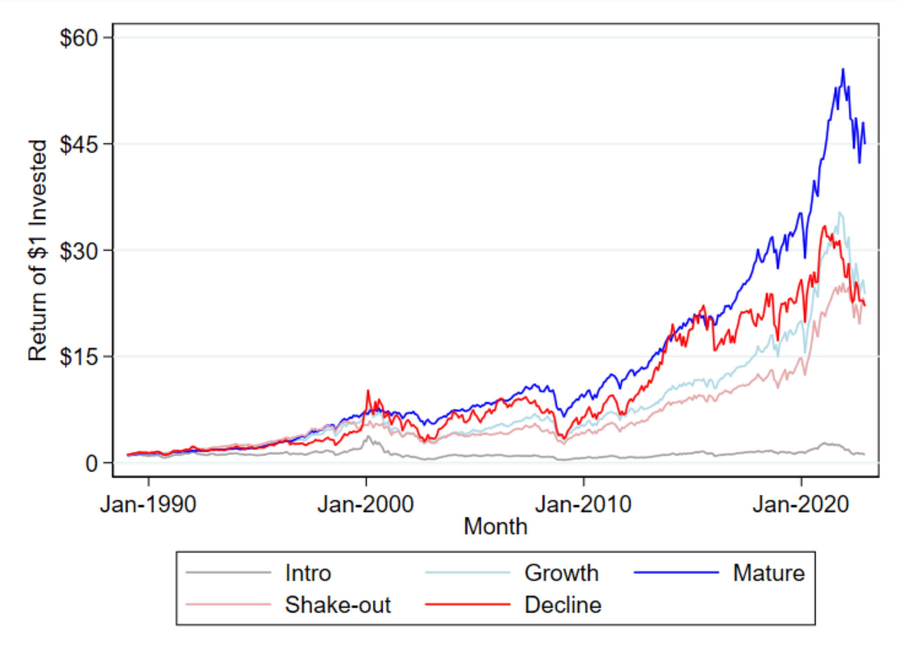
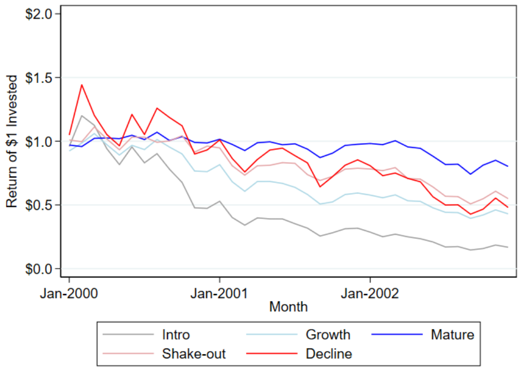
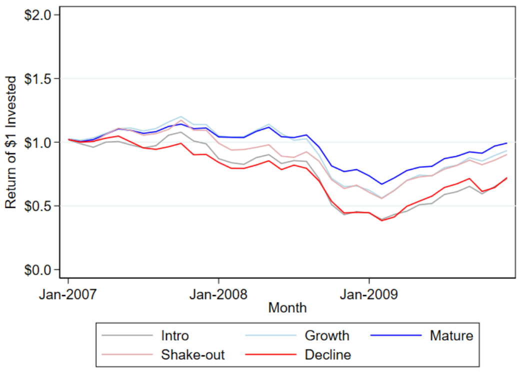


Figure 3: Buy-and-hold Return by Firm Life Cycle

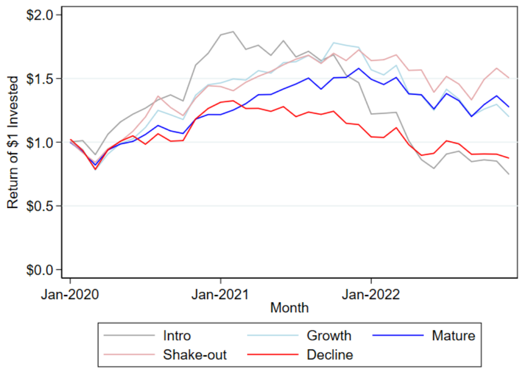
This figure shows the cumulative buy-and-hold return of value-weighted portfolios that invest into firms that are in a specific life cycle stage. The x-axis denotes the month and the y-axis denotes the cumulative return of $1 invested. All strategies start in January 1989 and end in December 2022.



(a) Dotcom Bubble



(b) Financial Crisis



(c) Corona Pandemic

Figure 4: Buy-and-hold Return in Subperiods

These figures show the cumulative buy-and-hold return of value-weighted portfolios that invest into firms that are in a specific life cycle stage. Panel A shows the performance during the bursting of the dotcom bubble (January 2000 - December 2002), Panel B shows the performance during the financial crisis (January 2007 - December 2009), and Panel C shows the performance during the corona pandemic (January 2020 - December 2022). The x-axis denotes the month and the y-axis denotes the cumulative return of $1 invested.

Table 1: Firm Life Cycle and Cash Flows

This table 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.

Cash flows from...	1 Intro	2 Growth	3 Mature	4 Shake-out	5 Shake-out	6 Shake-out	7 Decline	8 Decline
operating activities	-	+	+	-	+	+	-	-
investing activities	-	-	-	-	+	+	+	+
financing activities	+	+	-	-	+	-	+	-

Table 2: Companies by Firm Life Cycle

This table shows exemplary firms for each life cycle stage as of December 2022. The classification of firm life cycles follows Dickinson (2011). We show the firms with the largest market capitalization for each stage.

Life Cycle Stage	Examples
Intro	Uber Technologies, Alnylam Pharmaceuticals, Coupang
Growth	Amazon, Nvidia, Merck & Co
Mature	Apple, Microsoft, Alphabet
Shake-out	Berkshire Hathaway, Amgen, General Electric
Decline	Boeing, Seagen, Inspire Medical Systems

Table 3: Summary Statistics

This table shows summary statistics for firms in specific life cycle stages. Market cap is the total market capitalization (in billion USD). Assets is the total asset value (in billion USD) 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.

	Intro	Growth	Mature	Shake out	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

Table 4: Sharpe Ratios

This table shows the annualized excess return of value-weighted portfolios that invest into firms that are in a specific life cycle stage. In addition, the table shows the annualized standard deviation. The excess returns and standard deviations are expressed in percentage. 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.

	(1) Intro	(2) Growth	(3) Mature	(4) Shake-out	(5) Decline
Excess Return (annualized)	1.61	8.81	9.99	8.31	10.77
SD (annualized)	27.76	18.73	13.98	17.47	27.70
Sharpe ratio	0.07	0.47	0.71	0.47	0.39

Table 5: Factor Loadings

This table shows factor loadings of value-weighted portfolios that invest into 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 hundred 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.

	(1) Intro	(2) Growth	(3) Mature	(4) Shake out	(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

Table 6: Transition Matrix

This table shows transition probabilities across life cycle stages in Panel A. The columns indicate the current life cycle stage and the rows indicate the previous life cycle stage. Further, this table shows the probabilities of leaving the CRSP database due to merger (delisting code with 2 as first digit), exchange (delisting code with 3 as first digit), and liquidation (delisting code with 4 as first digit) in Panel B. In addition, it shows the probability of a stock leaving the CRSP database due to the exchange dropping the firm (delisting code with 5 as first digit). All numbers are expressed in percentage terms.

Previous \ Current	Intro	Growth	Mature	Shake-out	Decline
Panel A: Transition Matrix					
Intro	50.89	13.58	11.95	7.28	16.30
Growth	8.55	48.38	33.50	6.84	2.72
Mature	4.77	23.46	61.38	8.50	1.89
Shake out	11.67	18.28	36.95	23.92	9.18
Decline	30.84	9.22	9.00	10.78	40.16
Panel B: Delistings					
Merger	0.94	1.46	1.29	1.34	1.05
Exchange	0.01	0.04	0.04	0.01	0.05
Liquidation	0.03	0.01	0.00	0.01	0.06
Dropped from Exchange	1.73	0.47	0.40	1.33	1.90

Table 7: Fama and MacBeth (1973) Regressions

This table shows factor risk premiums across life cycle stages. We use cross-sectional Fama and MacBeth (1973) regressions in the spirit of Brennan et al. (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 calculate beta in rolling window regressions using 60 months of data. We use the market factor provided on Ken French's website (value-weighted return of all NYSE, AMEX, and NASDAQ stocks) as our market index. We calculate the other firm characteristics by following Fama and French (2015a,b). 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 percentage.

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Intro	Growth	Mature	Shake-out	Decline
Beta	0.08	0.12	0.14	0.11	0.06	0.22*
	(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***
	(-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***
	(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
	(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***
	(-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
	(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)
Standardization by LC	No	Yes	Yes	Yes	Yes	Yes
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

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Expected Return Sorts

This table shows monthly excess returns for portfolios 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 into 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").

	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	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Expected Return Sorts By Life Cycle

This table shows monthly excess returns for life cycle portfolios 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 into stocks with high expected returns and shorts stocks with low expected returns. All returns are value-weighted. We estimate risk premiums in monthly cross-sectional regressions with an expanding window ("point in time"). The portfolio break points are the same as in Table 8.

	Low	2	3	4	High	HML	t-statistic
Panel A: Intro							
Unconditional	-0.42	0.22	0.40	0.49	0.87	1.29***	3.69
Conditional	0.08	0.41	0.68	0.54	1.17	1.09	1.50
Difference						0.20	
t-statistic						0.28	
Panel B: Growth							
Unconditional	0.61	0.99	0.94	0.97	1.10	0.49*	1.77
Conditional	0.45	0.59	0.77	0.96	1.66	1.21***	3.26
Difference						-0.72**	
t-statistic						-2.40	
Panel C: Mature							
Unconditional	0.75	1.03	1.02	1.03	1.19	0.44*	1.85
Conditional	0.74	0.86	0.95	1.06	1.16	0.41	1.62
Difference						0.02	
t-statistic						0.24	
Panel D: Shake-out							
Unconditional	0.54	0.81	0.82	0.76	1.04	0.50	1.37
Conditional	0.64	0.84	0.73	0.70	1.11	0.47	1.38
Difference						0.03	
t-statistic						0.18	
Panel E: Decline							
Unconditional	1.01	0.96	0.10	0.59	1.05	0.07	0.14
Conditional	0.73	0.95	0.20	0.66	1.22	0.50	1.50
Difference						-0.44	
t-statistic						-1.01	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$