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The Effect of the Fama-French Five Factors on the Stock Returns of Nasdaq, NYSE, and AMEX-Listed IPO Firms: A Comparative Analysis Across Two Post-IPO Phases

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Abstract:

Since the early 1990s, factor investing has become central to equity research and investment practice, yet little is known about how well common risk factors explain the returns of newly listed firms or how this changes as they mature. This thesis examines whether the explanatory power of the Fama–French five-factor (FF5) model for US IPOs increases as firms season in public markets. Using newly listed firms on Nasdaq, AMEX, and the NYSE between 1990 and 2010, these firms are sorted into two cohorts based on time since listing (2–6 vs. 6–10 years post-IPO), and factor loadings, alphas, model fit, factor correlations, and spanning tests are analysed. The results show only modest improvements in model fit and factor structure over time. Profitability and investment contain more independent pricing information and market betas rise, but other loadings remain unstable and often insignificant – so the FF5 model appears to explain IPO returns somewhat better as firms mature, although the evidence is tentative and should be interpreted with caution.

Abstract (German):

Seit Anfang der 1990er Jahre hat sich Faktor-Investing zu einem wichtigen Bestandteil der Aktienanalyse und der Anlagepraxis entwickelt. Trotzdem ist noch wenig darüber bekannt, wie gut gängige Risikofaktoren die Renditen neu börsennotierter Unternehmen erklären können und wie sich dies im Laufe ihrer Entwicklung verändert.

Diese Arbeit untersucht, ob die Erklärungskraft des Fama-French-Fünf-Faktoren-Modells (FF5) für US-Börsengänge zunimmt, je länger die Unternehmen an den öffentlichen Märkten gelistet sind. Betrachtet werden Unternehmen, die zwischen 1990 und 2010 an der Nasdaq, der AMEX und der NYSE neu notiert wurden. Sie werden nach der Zeit seit ihrer Notierung (2–6 Jahre vs. 6–10 Jahre nach dem IPO) in zwei Gruppen eingeteilt. Anschließend werden Betas, Alphas, Faktorkorrelationen und Spanning-Tests analysiert.

Die Ergebnisse zeigen, dass sich die Modellgüte und die Faktorstruktur im Zeitverlauf nur leicht verbessern. Die Faktoren Rentabilität und Investitionen liefern zunehmend unabhängige Preisinformationen, und die Marktbetas steigen. Andere Faktorladungen bleiben jedoch instabil und oft statistisch unbedeutend. Insgesamt deutet dies darauf hin, dass das FF5-Modell die IPO-Renditen mit zunehmender Reife der Unternehmen etwas besser erklärt – die Befunde sind jedoch vorläufig und sollten vorsichtig interpretiert werden.

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List of Abbreviations:

AMEX American Stock Exchange

AT Total assets

B/M Book-to-market ratio

BE Book equity

CAPM Capital Asset Pricing Model

CEQ Common equity

CMA Conservative Minus Aggressive (Investment Factor)

COGS Cost of Goods sold

CRSP Center for Research in Security Prices

DDM Dividend Discount Model

EMR Excess Market Return

ETF Exchange-traded Fund

FF3 Fama–French three-factor model

FF5 Fama–French five-factor model

FRED Federal Reserve Economic Data

GDP Gross Domestic Product

GRS Gibbons–Ross–Shanken Test

GVKEY Global Company Key (firm identifier in Compustat)

HML High Minus Low (value factor)

INTEXP Interest expense

INV Investment (asset growth)

IPO Initial public offering

MC Market capitalization

MCAP Market capitalization

Nasdaq National Association of Securities Dealers Automated Quotations

NBER National Bureau of Economic Research

NYSE New York Stock Exchange

OP Operating profitability

PROF Profitability (characteristic used for portfolio sorts)

REV (Total) revenues

Rf Risk-free rate

Rm Market return

RMW Robust Minus Weak (profitability factor)

ROA Return on assets

SG&A Selling, General and Administrative expenses

SMB Small Minus Big (size factor)

US United States (of America)

USD United States dollar

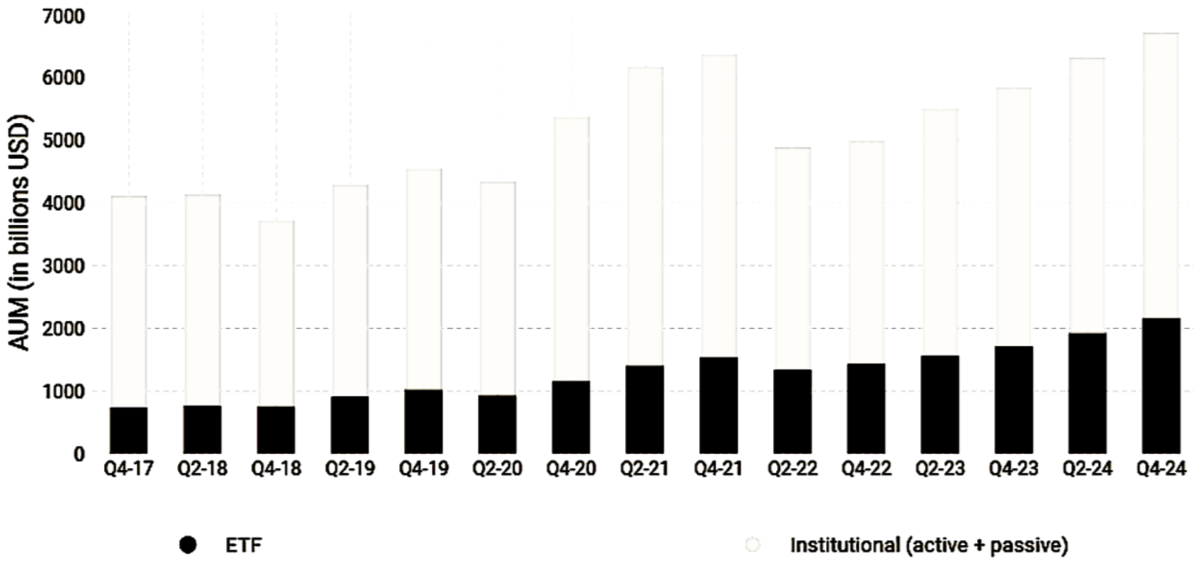
WRDS Wharton Research Data Services

1. Introduction

Over the past half-century, equity markets have become increasingly important in the global economy. The total market capitalization of listed firms, relative to world GDP, has risen from roughly 27 % in the mid-1970s to almost 130 % in 2024 (World Federation of Exchanges database, 2025)(See Appendix, Figure 1). This expansion shows that equity markets have grown faster than the real economy, reflecting a broader structural transformation in global finance. Well-developed capital markets have become a cornerstone of modern financial systems. As a globally accessible, self-pricing system, the stock market enables the efficient allocation of resources, improves transparency through market discipline, and supports financial stability. For firms, capital markets offer essential financing advantages. By issuing equity or debt securities, companies can raise funds directly from investors and reduce their reliance on banks. Moreover, higher market valuations can improve the terms of bank borrowing by making firms appear more creditworthy. Capital markets are thus a key driver of corporate investment and sustainable economic development. Likewise, governments rely heavily on bond markets as their main source of external financing. From the investor's perspective, capital markets offer an efficient way to allocate savings. Investors can buy firms' shares or bonds to construct diversified, liquid portfolios that provide the opportunity to participate in the development of a single company or many firms simultaneously. The associated risk is compensated by the market through dividends, interest, and capital gains from companies and governments. This excess return is called the risk premium (Demirgüci-Kunt & Levine, 1996).

Against this background, the question of how investors can systematically earn and manage equity risk premia becomes particularly important. In today's asset-management environment, factor strategies play a central role, enabling investors to systematically exploit risk premia and generate excess returns over the long term. In simple terms, these strategies overweight stocks that share certain measurable traits – for example, being cheap (value), small (size), or highly profitable – that have historically been associated with higher returns. Major providers such as Dimensional Fund Advisors, BlackRock (iShares), and Vanguard have integrated factor investing principles into their product design. Over the past decade, assets in factor-based strategies across institutional and wealth segments rose about 50% – from roughly USD 4 trillion to over USD 6 trillion across active funds, index funds, and ETFs, as the graph below shows (Abhishek Gupta, 2025, pp. 6-7).

Figure 1: Development of factor-based investment products



Source and representation: (Abhishek Gupta, 2025, p. 7)

The increasing importance of global capital markets for both firms and investors, together with the rising practical relevance of factor investing, motivates this thesis. Academic research provides the theoretical foundation of factor strategies. Among the pioneers in the field of asset pricing are Fama and French. The theoretical insights of the Fama–French frameworks are applied to the design of real-world investment strategies and products very frequently, which is evidenced by the fact that Kenneth French serves as co-chair of Dimensional Fund Advisors' Investment Research Committee (Advisors, 2025). Despite the widespread practical and academic use of factor models, their effectiveness across specific market segments and stages of firm maturity has received little attention. Most studies examine broad indices or entire markets without accounting for firm age or time since listing as potential determinants of factor behaviour. One remarkably underexplored segment is IPO firms. While both IPOs and factor models are well researched, they are rarely studied jointly. Existing contributions that bring them together generally compare IPOs to mature firms, rather than analysing how the factor loadings of the IPO firms themselves develop as the firms age and their characteristics change. To address this specific research gap in asset pricing theory, this thesis applies the Fama–French five-factor asset-pricing model to US IPO firms. This study investigates how the explanatory power and factor structure of the FF5 model change as IPO firms mature after going public. The central research question is:

Does the Fama–French five-factor model explain stock returns of IPO firms better in their later post-IPO years than in their early post-IPO years?

The methodology to answer the question is twofold. First, I conduct an extensive literature review that traces the emergence and development of the model. Second, I employ an empirical model and test hypotheses that address the problem at both macro and micro levels, drawing on existing literature. These hypotheses are discussed in more detail in Section 3.1. For the empirical analysis, I modify the Fama–French five-factor framework by forming two event-time cohorts for IPO firms (years 2–6 and 6–10 after the IPO) and estimating time-series regressions for each cohort. This approach allows me to compare IPO firms at two different post-listing stages in terms of their excess returns on the five factors, as well as differences in model fit, alphas, and factor loadings across cohorts.

The thesis proceeds as follows. Section 2 reviews the literature, which motivates the choice of the FF5 model, and links it to the IPO setting. Section 3 describes hypotheses and the data used for the quantitative analysis, presents the methodology, and its underlying hypotheses. Then it presents the statistical tests and time-series regression results and discusses their implications. In section 4, the conclusion, including limitations and outlining avenues for future research, is presented.

2. Literature Review

This literature review of asset-pricing models is organized thematically: (i) Evolution of asset-pricing models and the FF5 framework, (ii) IPO-specific firm dynamics. This review emphasizes peer-reviewed finance research, with primary attention to articles in leading journals. Foundational books and working papers are cited only when widely referenced.

(i) Foundations were laid by Markowitz (1959), the founder of modern portfolio theory, who explored how investors should balance risk and return and argued that stock return as well as risk characteristics shouldn't be assessed individually – instead, portfolios of securities should be valued. "If correlation among security returns were 'perfect' – if returns on all securities moved up and down together in perfect unison – diversification could do nothing to eliminate risk. The fact that security returns are highly correlated, but not perfectly correlated, implies that diversification can reduce risk but not eliminate it." (Markowitz, 1959, p. 5). This core idea of reducing unsystematic risk (specific risk of an asset) due to diversification while maintaining the same expected return was a milestone in portfolio theory.
In 1964 – 1965, William F. Sharpe and John Lintner built on this work and introduced the Capital Asset Pricing Model (CAPM) – a single-factor model. The model extends Markowitz's portfolio theory by introducing the concept of beta (β), which measures how strongly an asset's return covaries with the return on the market portfolio. If β = 1, the asset tends to move in line with the market; if β > 1, it amplifies market movements, and if β < 1, it varies less than the market. The model shows that, in equilibrium, the expected return on an asset depends only on its covariance with the market portfolio. Assets with higher market covariance carry greater systematic risk and therefore require higher expected returns. In this sense, investors are compensated according to an asset's contribution to the overall risk of the market portfolio. Expressed mathematically, Equation (1) states that the expected return ($\mathrm{E}R_i$) on an asset equals the risk-free rate (R_f) plus its beta (β_i) times the market risk premium ($\mathrm{E}R_m - R_f$) (Sharpe, 1964) (Lintner, 1965).

$$\mathrm{E}R_i = R_f + \beta_i\left(\mathrm{E}R_m - R_f\right)$$
$$\mathrm{E}R_i = Expected\ Return\ of\ Investment$$
$$R_f = Risk - free\ Rate$$
$$\beta_i = Systematic\ risk\ of\ the\ Investment$$
$$\left(\mathrm{E}R_m - R_f\right) = Market\ Risk\ Premium$$

The CAPM is still used for cost of capital, portfolio performance, and risk-adjusted return calculations. It provides a clear, intuitive framework for linking risk and expected return. However, the model has faced criticism for its restrictive assumptions, including risk-averse and mean-variance optimizing investors with homogeneous expectations, a single-period horizon, frictionless markets without taxes or transaction costs, perfectly divisible and marketable assets, price-taking behaviour, and the ability of all investors to borrow and lend unlimited amounts at a common risk-free rate.

Black et al. (1972) show that the CAPM's central prediction, that expected returns are strictly proportional to beta, does not hold empirically. Their data on NYSE securities from 1926 to 1966 show that high-beta stocks earned lower returns and low-beta stocks earned higher returns than the model predicts, concluding the relationship between risk and return was weaker than CAPM suggests (Black, et al., 1972).

Fama and MacBeth (1973) also examined whether the CAPM's prediction of a linear relationship between expected return and market beta holds in real data. Their findings on NYSE securities from 1926 to 1968 provided partial support for the model, as average returns tended to increase with beta. However, they also discovered significant limitations: beta estimates were often unstable and imprecise, causing measurement errors, and a large share of return variation remained unexplained by beta alone. This implied that asset returns need to be driven by additional factors beyond market risk (Fama & MacBeth, 1973).

Fama and French (1992) revisited the CAPM using Nasdaq, AMEX, and NYSE data from 1963 to 1990. They analysed whether firm characteristics such as market beta, size, leverage, earnings-price ratio, and book-to-market equity explain differences in stock returns. Their results show that the traditional CAPM relationship between beta and average return is weak. Instead, they discovered that small firms and firms with high book-to-market ratios earn higher average returns and explain much of the cross-sectional variation in returns, while beta, leverage, and earnings-price lost importance (Fama & French, 1992).

Building on these findings, Fama and French (1993) introduced the three-factor model. In addition to the market factor, they added two new factors: the SMB (Small Minus Big) factor, which represents the return difference between portfolios of small and large firms. It captures the idea that, on average, smaller companies are riskier and therefore earn higher returns than large-cap stocks, reflecting a size premium. Secondly, the HML (High Minus Low) factor measures the return difference between portfolios of high- and low-book-to-market firms, which are considered value and growth stocks, respectively. Value stocks typically trade at lower prices relative to their fundamentals and are considered riskier by the market compared to growth stocks. According to asset pricing theory, investors require higher expected returns as compensation for bearing higher risk, which explains the long-term outperformance of value stocks relative to growth stocks. Fama and French demonstrated that incorporating these two additional factors, along with the traditional market factor, significantly improved the model's ability to explain variations in average stock returns relative to the single-factor CAPM. In their US sample (1963–1991), both SMB and HML exhibited positive average premiums, providing strong evidence of size and value effects in stock returns. This framework laid the foundation for the later developed FF5 model. (Fama & French, 1993).

Four years later, Daniel and Titman (1997) argued that although company size and book-to-market ratio are strongly correlated with average stock returns, these correlations cannot be explained by an exposure to non-diversifiable risk factors, as assumed by Fama and French (1993). Instead, they argue that the return premiums for small-cap and value stocks arise from the characteristics of the companies themselves. In other words, firm characteristics such as size, book-to-market ratio, profitability, or investment directly influence expected returns because they reflect how the market perceives and prices individual firms, rather than capturing firms' sensitivity to shared risk factors. (Daniel & Titman, 1997).

In 2000, Davis et al. re-examined the Fama and French three-factor model using a much longer US sample (1929 – 1997) and found that the relationships between size, book-to-market ratios, and average returns remain stable and robust over time. Moreover, they show that differences in average returns are better explained by factor loadings on the Fama–French factors than by characteristics alone. This evidence is more consistent with a risk-based interpretation of the size and value premia and therefore challenges the "characteristics-only" view of Daniel and Titman (1997) (Davis, et al., 2000).

Carhart (1997) extended the Fama–French three-factor framework by adding a fourth factor that captures the momentum effect. His empirical analysis of mutual funds demonstrated that including past return performance (momentum) as a stock Return driver increases the model's ability to explain cross-sectional returns and fund performance (Carhart, 1997).

Griffin (2000) examines various geographical variants of the Fama-French three-factor model, global, international, regional, and country-specific approaches, in terms of their explanatory power for stock returns. His results show that country-specific models provide the highest explanatory power, while global models often lead to large pricing errors. These findings empirically suggest that asset pricing models should primarily be adapted to local market conditions (Griffin, 2002).

Also, Fama and French (2012) extended their analysis to an international context. They analyse 23 developed markets and test both the three-factor model and Carhart's extended four-factor model. The results show that there are common patterns in size, value, and momentum premiums worldwide, but that regional differences are not adequately captured by global models. This is particularly evident in the lack of a momentum effect in Japan (Fama & French, 2012).

In 2003, Titman et al. investigated the relationship between corporate investment intensity and future stock performance. Their results indicate that firms with rising capital expenditures generally experience lower benchmark-adjusted returns in the subsequent five years, implying that higher investment may signal reduced expected returns. (Titman, et al., 2003). Ten years later, Novy-Marx (2013) demonstrated that profitability, measured by the ratio of gross profits to assets, has a similarly strong predictive power for average returns as the book-to-market ratio. Highly profitable firms achieve higher returns despite higher valuation ratios. Incorporating this measure improves the performance of value strategies, particularly among large, liquid stocks (Novy-Marx, 2013).

The empirical results on investment and profitability had not been considered as key return drivers in the three- and four-factor models to date. Motivated by these findings, Fama and French expanded their three-factor model by adding the profitability and investment factors and introduced their FF5 model in 2015. The theoretical foundation for this extension lies in the dividend discount model (DDM), originally formulated by Williams (1938) and later linked to firm fundamentals by Miller & Modigliani (1961). The DDM states that the market value of a firm's share (m_t) at time (t) equals the present value of its expected future dividends $E\left[d_{\{t+\tau\}}\right]$ discounted by $(1+r)^{\tau}$, the long-term expected rate of return:

$$m_t = \Sigma_{\{\tau=1\}}^{\infty} \frac{E\left[d_{\{t+\tau\}}\right]}{(1+r)^{\tau}}$$

(Williams, 1938). Fama and French restate the dividend-discount model, following Miller & Modigliani (1961), by replacing expected dividends with expected equity earnings ($Y_{\{t+\tau\}}$) net of expected changes in book equity ($\Delta B_{\{t+\tau\}}$) between time points ($t+\tau$) and ($t+\tau-1$), so that the market value satisfies:

$$M_t = \Sigma_{\{\tau=1\}}^{\infty} \frac{E\left[Y_{\{t+\tau\}} - \Delta B_{\{t+\tau\}}\right]}{(1+r)^{\tau}}$$

(Miller & Modigliani, 1961). If we then divide both sides by the book value (B_t) at the valuation date (t) we obtain:

$$\frac{M_t}{B_t} = \frac{\frac{\Sigma_{\{\tau=1\}}^{\infty} E\left[Y_{\{t+\tau\}} - \Delta B_{\{t+\tau\}}\right]}{(1+r)^{\tau}}}{B_t}$$

It becomes clear that – ceteris paribus – a higher book-to-market ratio $\left(\frac{\mathrm{B_t}}{\mathrm{M_t}}\right)$ indicates a lower market value relative to the accounting value of its equity. Suppose two firms have similar book equity and comparable expectations about future cash flows, but one trades at a lower market price; the discount rate $(1+r)^{\tau}$ required by investors for that firm must be higher. This is evident in the equation above. Put differently, a firm with a high book-to-market ratio can be interpreted as cheap or undervalued relative to its accounting fundamentals. Investors are only willing to hold it at a low price because of higher perceived risk (for example, more volatile or cyclical earnings, distress risk, or uncertain investment opportunities) or pessimistic expectations that depress the price. In an efficient market, this lower price does not represent a free lunch, rather, it reflects the higher return investors expect to bear the additional risk or uncertainty associated with such firms. Thus, within the dividend discount model, a high book-to-market ratio naturally corresponds to higher expected returns and provides the theoretical foundation for the value effect documented by Fama and French (Fama & French, 1993). Conversely, a stronger expected investment ($\Delta B_{\{t+\tau\}}$) leads to a lower expected return. It means that a larger proportion of future profits will be retained and reinvested in the company rather than distributed. In the valuation equation, this leads to a decrease in the available surplus $\Sigma_{\{\tau=1\}}^{\infty} E\left[Y_{\{t+\tau\}} - \Delta B_{\{t+\tau\}}\right]$, which, for a given observed market value, implies a lower discount rate $(1+r)^{\tau}$ and therefore lower expected returns. By contrast, a stronger expected profitability, reflected in higher expected equity earnings ($Y_{t+\tau}$) leads to a higher expected return. For a given expected investment ($\Delta B_{t+\tau}$), an increase in ($Y_{t+\tau}$) raises the surplus term ($Y_{t+\tau} - \Delta B_{t+\tau}$) in the valuation equation. This implies that the present value of expected future distributions to shareholders increases. To keep this higher stream of cash flows consistent with the observed market value, the discount rate $(1+r)^{\tau}$ in the dividend discount model must increase, which corresponds to a higher expected return. Accordingly, firms with higher expected profitability produce more cash flow per unit of book equity, resulting in higher expected returns. These theoretical relations between expected returns, book-to-market, profitability, and investment directly motivate an extension of the classic Fama–French three-factor model, adding two additional factors:

- Profitability (RMW): “Robust minus Weak” measures the difference in average returns between portfolios of firms with high versus low operating profitability
- Investment (CMA): “Conservative minus Aggressive” captures the difference in average returns between portfolios of firms with low and high investment growth

With this addition, the five-factor model not only explains market, size, and value effects, but also systematically considers how profitability and investment characteristics affect stock returns (Fama & French, 2015).

(ii) Having outlined the development of modern asset-pricing models and the rationale for adopting the Fama–French five-factor framework, the focus now shifts to what the existing literature reveals about IPO firms. In particular, the following section reviews empirical evidence on how newly listed companies differ from seasoned firms in terms of return drivers, risk characteristics, and stock market behaviour, and how these differences shape their post-IPO performance. Firms exhibit high idiosyncratic variance and unstable factor exposures in the early years after their IPO. As firms season, more stable, systematic patterns emerge. A potential reason, besides the low level of awareness of IPO firms, might be that they differ systematically from established firms in terms of firm characteristics: they generally have lower profitability, higher investment rates, and lower book-to-market ratios than size-matched companies. Furthermore, IPO firms experience a significant decline in operating performance and valuation ratios during the three years following the IPO, including decreases in operating profitability, market-to-book ratios, price–earnings ratios, and earnings per share (Jain & Kini, 1994).

Using a sample of 4,753 US operating-company IPOs issued between 1970 and 1990 and matched to non-issuing firms of similar size, Loughran and Ritter (1995) show that firms going public are poor long-run investments: the average return on IPO firms is about 5% per year over the five years after issuance, compared to about 12% for their size-matched non-issuers, implying that an investor would have to invest approximately 44% more money in issuers than in non-issuers of the same size to have the same wealth five years after the offering date. This suggests that size signals are muted in young IPOs and only gain explanatory power with increasing maturity (Loughran & Ritter, 1995). Empirical evidence shows that the market beta of young companies is initially inflated and unstable, only approaching its long-term level over time.

Chincarini et al. (2020) report that betas reach values of around 1.6 – 1.7 shortly after the IPO and move towards 1.0 within approximately 10 – 15 years. In the early years, strong idiosyncratic volatility also dampens the observed market correlation. As idiosyncratic variance decreases, the relative contribution of systematic market risks to return variation increases – the market effect should be more pronounced in later IPO years than in the early phase (Chincarini, et al., 2020).

For the size premium, Brav et al. (1998) show that it has only limited explanatory power in the early post-IPO years – typically within the first five years. The reason is the dominance of idiosyncratic, company-specific fluctuations, which dilute the statistical relationship between company size and expected returns. As the listing period increases, this idiosyncratic dominance decreases. The size effect becomes more stable and measurable, and gains in significance (Brav, et al., 1998).

In 2025, Ritter shows that companies that have been listed for at least five years achieve higher returns of approximately 2.1% p.a. on average over five years than newly listed companies, with comparable size and similar B/M-ratio. This suggests that value signals are muted in young IPOs and only gain explanatory power with increasing maturity (Ritter, 2025).

Veronesi (2002) developed a theoretical model showing that newly listed firms experience a period of high uncertainty after going public because investors must learn about the firm's true profitability and risk. During this "learning phase," stock prices and returns primarily reflect this uncertainty rather than fundamental performance differences. As information accumulates over time, the uncertainty declines, and firm-specific characteristics – like profitability – begin to play a more significant role in explaining returns (Veronesi, 2002).

In summary, as IPO firms mature, idiosyncratic risk declines and factor exposures become more stable, allowing asset-pricing models to capture return variation better. However, the extent to which this explanatory power evolves across firms by the time they are listed and the specific factors that drive these changes, remain insufficiently explored. This literature gap lays the groundwork for the following section, which addresses the practical motivation and the literature together and explains why the topic was chosen.

3. Empirical Analysis

3.1 Hypotheses

Before conducting the empirical analysis, it is essential to clarify the underlying hypotheses. They refine the rather macro research question: "Does the Fama–French five-factor model explain stock returns of IPO firms better in their later post-IPO years than in their early post-IPO years" into more micro-level expectations about how individual stock return driving factor loadings and model fit evolve as IPO firms mature. As discussed in the literature review, the Fama–French five-factor model explains stock returns using several systematic drivers: investment, profitability, size, the book-to-market (value) ratio, and the excess market return. The corresponding factor loadings are interpreted as the firm's exposures to these underlying sources of risk. In this study, the empirical analysis compares the estimated factor loadings of those factors, their statistical significance, and the overall explanatory power (adjusted R^2) of the model for US IPO firms listed on Nasdaq, AMEX, and NYSE as these firms mature.

To capture different stages of the post-IPO life cycle, two cohorts are constructed: firms are assigned to Cohort 1 when they have been listed for 2–6 years and to Cohort 2 when they have been listed for 6–10 years. This design ensures that the same firms can be compared with respect to their factor exposures at different stages of their post-IPO life. Building on the existing literature, it is expected that IPO returns become increasingly aligned with systematic risk factors as firms age, leading to greater model explanatory power and shifts in the relevance and significance of individual factors. This yields the following hypotheses:

- **H_1:** The overall explanatory power of the five-factor model is higher for Cohort 2 than for Cohort 1
- **H_2-a:** The market effect (exposure to systematic market risk) increases for Cohort 2 compared to Cohort 1
- **H_2-b:** The size effect increases for Cohort 2 compared to Cohort 1

◦ **H_2-c:** The value effect increases for Cohort 2 compared to Cohort 1

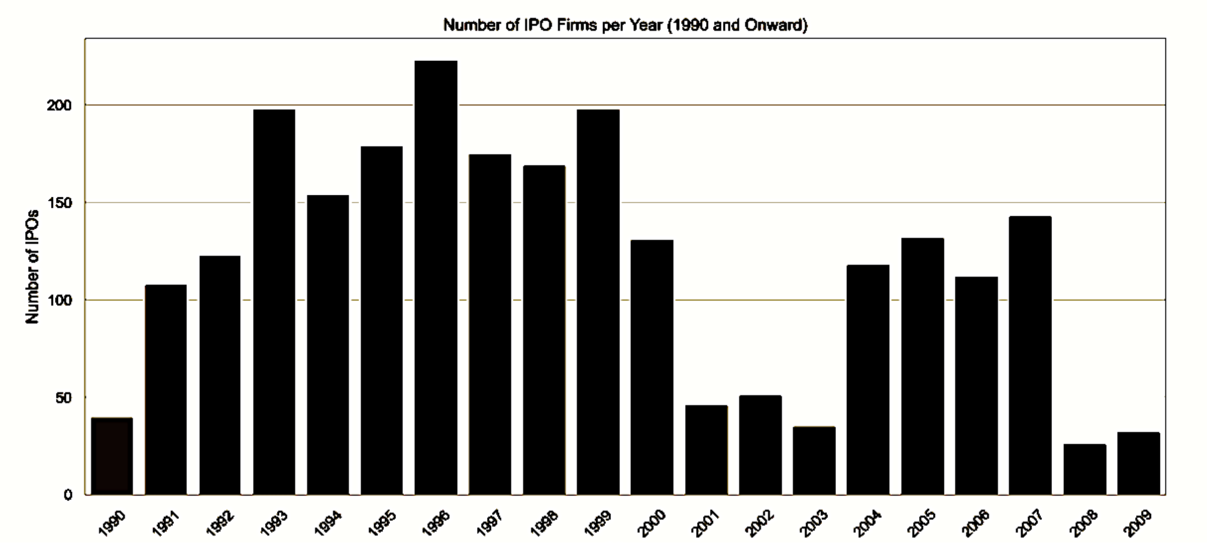
◦ **H_2-d:** The profitability effect increases for Cohort 2 compared to Cohort 1

◦ **H_2-e:** The investment effect increases for Cohort 2 compared to Cohort 1

3.2 Data

For the empirical analysis, I follow the FF5 approach. First, I download monthly market capitalizations, total stock returns (with dividends reinvested), and the equal-weighted market return for Nasdaq, AMEX, and NYSE from CRSP, as well as accounting data (total assets, total revenue, cost of goods sold, SG&A, interest expense, common equity) from Compustat. For the risk-free rate, I use the 3-month US Treasury bill from FRED. The sample covers all firms that went public on Nasdaq, AMEX, and NYSE between 1990 and 2010. In total, the sample includes approximately 2,300 companies, as shown in the figure below.

Figure 2: Annual distribution of IPO firms in the sample



Source and representation: Own elaboration

For each firm, I track data from 1990 to 2020. The period starts in 1990 because earlier IPO activity is rare, and the analysis excludes the post-2020 period to avoid biases caused by COVID-19.

Following a two-step procedure, first, I pull monthly market data from CRSP for all firms listed on Nasdaq, AMEX, and NYSE, and use the "include all companies of the exchange" option to export the corresponding GVKEYs. I then upload this GVKEY list to Compustat and obtain the financial statement data for exactly these firms. This ensures a consistent firm set across both databases (Stanford University, 2025).

After importing the data into Excel, I apply two filters. First, I exclude micro-caps with a market capitalization below USD 100 million, measured two years after the IPO. Second, I require firms to survive at least ten years after listing. Firms that default or delist earlier are removed. Firm-year observations with missing accounting data are excluded from the sample for that year. The firm characteristics used to construct the Fama–French factors (profitability, investment, size, and the book-to-market ratio) are calculated in Excel in June each year. The excess market return is determined monthly. All accounting data and market data besides the one for market return are always taken from December the year before; thus, $t-1$ refers to December of the prior year and $t-2$ to December two years earlier:

The excess market return (EMR): defined as the return on the equal-weighted US market portfolio minus the risk-free rate (three-month treasury bill rate):

$$MKT = Rm_t - Rf_t$$

Size (MC): proxied by market capitalization, calculated as:

$$SIZE = MCAP_{t-1} = Shareprice_{t-1} \cdot Shares\ Outstanding_{t-1}$$

Book-to-market (B/M): ratio of book equity to market capitalization at the end of December of the year $t-1$:

$$B/M = \frac{BE_{t-1}}{MC_{t-1}}$$

Book equity is proxied by common equity (CEQ), as IPO firms typically have no preferred stock and limited deferred tax data.

Operating profitability (OP): defined as total revenues minus cost of goods sold, selling, general, and administrative expenses, and interest expense, all divided by book equity:

$$OP = \frac{REV_{t-1} - COGS_{t-1} - SGA_{t-1} - INTEXP_{t-1}}{BE_{t-1}}$$

This variable measures how efficiently a firm converts equity into operating profits.

Investment (INV): calculated as the change in total assets between the two most recent fiscal year-ends, scaled by total assets from the year $t - 2$:

$$INV = \frac{AT_{t-1} - AT_{t-2}}{AT_{t-2}}$$

This captures the firm's asset growth and serves as a proxy for investment activity.

3.3 Methodology

Following the Fama–French (2015) methodology, I construct independently characteristic-sorted portfolios as test assets (dependent variables) and factor-mimicking portfolios (instead of individual stocks) as independent variables that proxy the underlying systematic factors driving stock returns. Their construction is explained in detail in the following. This averages out idiosyncratic noise, delivers more stable, interpretable factor loadings, and boosts statistical power. In contrast to the original value-weighted approach, this study uses equal-weighted portfolios. Fama and French (2008) note that value-weighted returns describe the market portfolio, while equal-weighted returns better capture the average behaviour of stocks (Fama & French, 2008, p. 1654). Loughran and Ritter (1995) also use equally weighted portfolios in their IPO study, where each firm receives the same investment amount. This avoids large IPOs dominating the results and reflects the average performance of issuing firms more accurately (Loughran & Ritter, 1995). Following their reasoning, every IPO in this sample contributes equally to portfolio returns, regardless of its market capitalization. This corresponds to investing the same amount in each company's stock rather than weighting investments by firm size. In this way, changes in factor exposures are captured equally across all firms, avoiding dominance by large IPOs and allowing a clearer view of how these exposures evolve as firms mature.

Before applying the Fama–French sorts, I group firms by event time, measured as IPO age. Firms are placed in Cohort 1 when they have been listed for 2–6 years, and in Cohort 2 when they are 6–10 years past their IPO. For example, a firm that went public in 1995 belongs to Cohort 1 from 1997 to 2001 and moves to Cohort 2 from 2001 to 2005. A firm with an IPO in 2000 is in Cohort 1 from 2002 to 2006 and in Cohort 2 from 2006 to 2010. By pooling firms by IPO age rather than calendar year, I can examine whether the impact of the Fama–French factors on returns varies as firms mature.

The following timing procedure ensures the implementation of the cohort approach. At the beginning of June (t_1), firms are sorted by accounting information from the fiscal year December (t_0), imposing a six-month information lag and held to May (t_{+1}). Monthly stock returns are recorded for all constituent firms from June through May. The portfolio's monthly return is the equal-weighted average of its constituents. This lag structure ensures investors could have observed the accounting data and could have acted – buying or selling the stocks – so return differences reflect past characteristics rather than look-ahead bias.

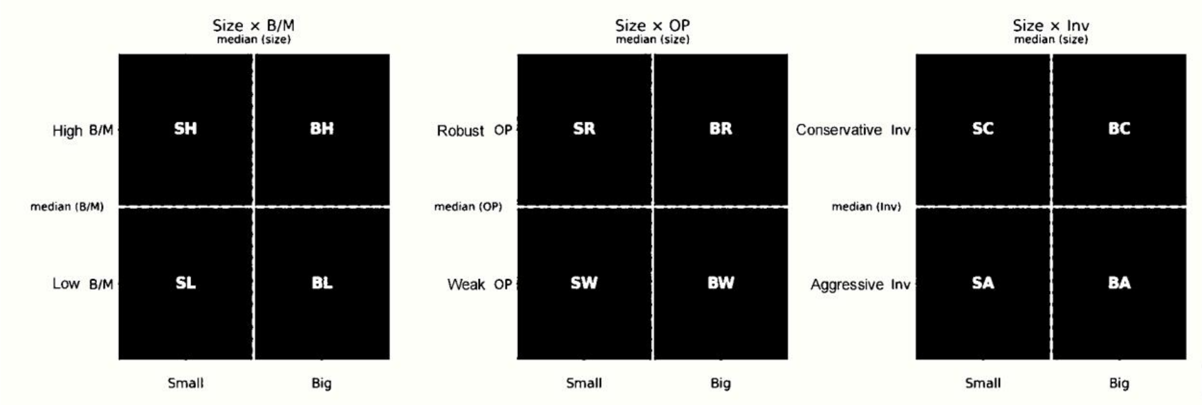
For illustration, all firms in the event year (t_2), after the IPO (firms were stock listed for 2 years), are sorted into portfolios in June, and the portfolios are then held from June (t_2) to May (t_3). The same rolling logic applies as firms progress through event years $(t_2 - t_9)$. The first sorting starts in (t_2), as the calculation of the investment factor requires total assets from December of the year and two years before (see section 4.1 data): here from $(t_1 - t_2)$ and $(t_0 - t_1)$. Obtaining reliable accounting data before the IPO for many firms is almost impossible. For the portfolio construction, I've chosen the independent 2x2 sort approach as recommended by Fama and French: "Armed with the evidence presented here, which version of the factors would we choose if starting fresh? We might prefer the factors from the 2 & 2 Size-B/M, Size-OP, and Size-INV sorts over those from the 2 & 3 sorts (the original approach)" (Fama & French, 2015, p. 19). The procedure of the portfolio construction each June $(t_2 - t_9)$ proceeds as follows. Firms are categorized by:

- Size: Firms are split into Small (S) and Big (B) using the cross-sectional median market capitalization
- Profitability: Firms are split into Robust (R) (high profitability) and Weak (W) (low profitability) using the median operating profitability
- Investment: Firms are split into Conservative (C) (low investment) and Aggressive (A) (high investment) using the median investment (asset growth)

◦ Value: Firms are split into High (H) and Low (L) using the book-to-market ratio: High corresponds to value (high B/M), Low to growth (low B/M)

We then independently sort firms by size (Small/Big) in combination with each of the three other characteristics (profitability – Robust/Weak, investment – Conservative/Aggressive, and value – High/Low). This procedure yields three 2×2 portfolios as shown in the graph below.

Figure 3: 2x2 Sorting Scheme for Factor-Mimicking Portfolios



Source and representation: Own elaboration

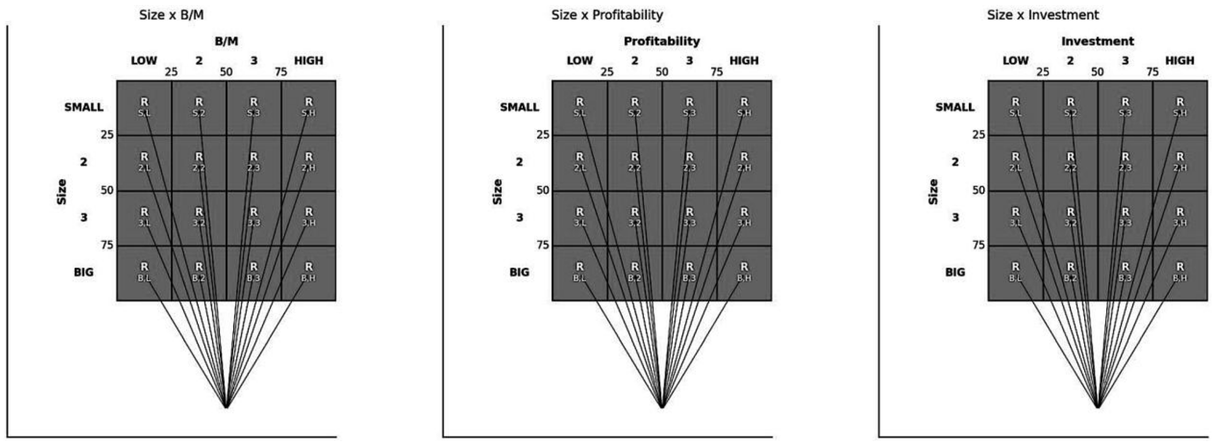
From these portfolios, the factor returns are constructed as monthly long-short spreads:

◦ SMB (Small minus Big): average monthly return of all Small portfolios minus average monthly return of all Big portfolios: $SMB = (SH + SL + SR + SW + SC + SA)/6 - (BH + BL + BR + BW + BC + BA)/6$
◦ HML (High minus Low): average monthly return of High portfolios minus average monthly return of Low portfolios: $HML = (SH + BH)/2 - (SL + BL)/2$
◦ RMW (Robust minus Weak): average monthly return of Robust portfolios minus average monthly return of Weak portfolios: $RMW = (SR + BR)/2 - (SW + BW)/2$
◦ CMA (Conservative minus Aggressive): average monthly return of Conservative portfolios minus average monthly return of Aggressive portfolios: $CMA = (SC + BC)/2 - (SA + BA)/2$

The explanatory variables are these constructed factor returns (SMB, HML, RMW, CMA) together with the market excess return, defined as the equal-weighted market return across Nasdaq, AMEX, and NYSE minus the three-month Treasury bill rate.

For the dependent variables, a similar procedure is used. Instead of building 2x2 portfolios, 4x4 portfolios were sorted independently. Instead of using the median as the breakpoint for the different portfolios, quantiles were used. So, in total, we get three 4x4 portfolios. The monthly average portfolio returns are adjusted for the three-month Treasury bill rate.

Figure 4: 4x4 Sorting scheme for test portfolios



Source and representation: Own elaboration

This approach identifies which stock types are most affected by changes in the explanatory variables. For example, it reveals whether high profitability has a more substantial impact on performance among small, aggressive firms than among big, conservative firms.

For each cohort, I estimate 48 separate time-series regressions, one for each test portfolio. Each regression is run over 48 monthly observations (4 years), so every test portfolio has its own regression using 48 months of returns. The factors (independent variables) are identical across all portfolios in a given month: in month t, the same set of factor returns is used for all 48 portfolios, while the dependent variable differs by portfolio. I also include time-fixed effects (month–year dummies) to absorb period-specific, economy-wide shocks (e.g., macro news, liquidity shifts, crises), so the coefficients are identified from cross-sectional variation rather than common shocks. The resulting regression function is:

$$R_{m(t)} - R_{f(t)} = \alpha + \beta \cdot [R_{m(t)} - R_{f(t)}] + s \cdot SMB_{(t)} + h \cdot HML_{(t)} + r \cdot RMW_{(t)} + c \cdot CMA_{(t)} + \varepsilon_{(t)}$$

This design allows testing whether the Fama-French five-factor model explains IPO returns more effectively as firms season.

3.4 Results

3.4.1 Factor Summary Statistics

In this section, I begin by outlining the empirical procedure. First, I report factor summary statistics (means, standard deviations, t-statistics) to show which premia are present in the sample and the scale of their volatility (see Appendix Table 1 for the full results). Then I present the correlation matrix of the factors. This highlights co-movements and potential multicollinearity, which is essential for interpreting factor loadings. Next, I run factor-spanning tests to assess factor redundancy before estimating the main model. Finally, I estimate the time-series regressions for the 48 portfolios. This sequence provides a clean foundation for the portfolio regressions that follow. First, the monthly factor returns are presented separately for Cohort 1 and Cohort 2 in the table below:

Table 1: Averages, standard deviations, and t-statistics for monthly returns

Cohort 1			
	Mean (%)	Std Dev (%)	t-Statistic
Rm-Rf	0.8905	1.4707	4.19
SMB	-0.0514	2.6141	-0.14
HML	0.3144	2.3252	0.94
RMW	-0.1514	2.0314	-0.52
CMA	0.3477	2.1317	1.13

Cohort 2

	Mean (%)	Std Dev (%)	t-Statistic
Rm-Rf	0.7039	2.3642	2.06
SMB	0.1967	3.7319	0.37
HML	0.1726	2.996	0.4
RMW	0.2031	2.1838	0.64
CMA	0.7291	2.0514	2.46

Source and representation: Own elaboration

In Cohort 1, the market excess return (Rm-Rf) is positive and statistically significant, indicating a reliable market premium. SMB, HML, CMA, and RMW have small means and low t-statistics. They are not statistically different from zero. Volatility is moderate across factors.

In Cohort 2, the market premium remains positive and significant, though its volatility increases. The investment factor (CMA) rises in mean and becomes statistically significant at conventional levels. All other factor means turn positive but remain statistically insignificant and therefore carry no economic interpretation.

Overall, only the market factor exhibits a consistent premium across both cohorts, and the investment effect becomes more pronounced, suggesting that investment-related risks become more relevant as firms mature. Size, value, and profitability premia are not evident in average monthly returns for these IPO cohorts. The lack of statistical significance for most factors likely reflects the short sample period and limited time-series variation within each cohort.

3.4.2 Correlation Matrix

I report pairwise correlations by cohort. They show how the five factors move together. Large absolute values flag potential multicollinearity. Small values indicate a cleaner, more orthogonal structure.

Table 2: Correlations between different factors

Cohort 1

	Rm-Rf	SMB	HML	RMW	CMA
Rm-Rf	1	0.04	0.22	-0.27	0.19
SMB	0.04	1	-0.59	-0.1	-0.01
HML	0.22	-0.59	1	-0.04	0.23
RMW	-0.27	-0.1	-0.04	1	-0.86
CMA	0.19	-0.01	0.23	-0.86	1

Cohort 2

	Rm-Rf	SMB	HML	RMW	CMA
Rm-Rf	1	0.34	-0.02	-0.19	0.14
SMB	0.34	1	-0.02	0.23	0.17
HML	-0.02	-0.02	1	0.08	0.16
RMW	-0.19	0.23	0.08	1	-0.42
CMA	0.14	0.17	0.16	-0.42	1

Source and representation: Own elaboration

In Cohort 1, the correlation between RMW and CMA is strongly negative (−0.86). This means that months in which the profitability factor (RMW) delivers high returns tend to coincide with low returns on the investment factor (CMA), and vice versa. This pattern is consistent with a trade-off often observed in early post-IPO firms: high investment paired with low current profitability, or the reverse. This is quite logical, as small newly listed firms usually reinvest a large share of their cash flows into growth opportunities and capital expenditures. Money that could show up as current earnings instead appears as investment on the balance sheet, which temporarily depresses measured profitability. The correlation between SMB and HML is also negative (−0.59), consistent with small firms in this cohort tending to be growth rather than value stocks. The remaining factor correlations are modest in magnitude. Taken together, these patterns point to potential multicollinearity among the factors.

In Cohort 2, the correlation between RMW and CMA weakens to about −0.42. This suggests that firms are more likely to remain profitable even while making substantial investments. The correlation between SMB and HML is near zero, indicating that size is no longer the decisive factor for whether a firm is classified as value or growth. The correlation between EMR and

SMB is modestly positive (0.34), which is plausible because small firms tend to be more pro-cyclical and exhibit higher market betas, so the small-minus-big spread comoves with the market. The remaining correlations are low. As firms mature, the factor structure becomes more orthogonal, with weaker cross-factor co-movement. This implies cleaner separation of factor effects and less idiosyncratic noise in returns, reducing multicollinearity and improving the precision of estimated loadings. The correlation evidence motivates the subsequent spanning tests and frames the portfolio regressions that follow.

3.4.3 Factor Spanning Test

Each factor is regressed on the remaining four to test redundancy (Huberman & Kandel, 1987). A statistically insignificant intercept (α ≈ 0) indicates the factor is spanned – adding it would not shift the mean–variance frontier or the tangency portfolio. A positive, significant intercept indicates an independent premium for that factor. R^2 shows how much month-to-month variation in the factor is explained by the others, but it does not determine spanning.

Table 3: Using four factors in regressions to explain average returns on the fifth

Cohort 1

	Int	Rm-Rf	SMB	HML	RMW	CMA	R^2
2x2 Factors							
Rm-Rf							
Coef	0.008		0.204	0.121	-0.312	-0.114	0.148
t-stat	4.120		3.182	1.566	-2.552	-0.908	
SMB							
Coef	-0.005	0.497		-0.384	0.619	0.556	0.224
t-stat	-1.568	3.182		-3.311	3.313	2.951	
HML							
Coef	-0.002	0.219	-0.283		0.460	0.538	0.174
t-stat	-0.687	1.566	-3.311		2.825	3.361	

	Int	Rm-Rf	SMB	HML	RMW	CMA	R^2
RMW							
Coef	0.005	-0.216	0.176	0.177		-0.665	0.490
t-stat	2.858	-2.552	3.313	2.825		-8.485	
CMA							
Coef	0.006	-0.079	0.158	0.207	-0.668		0.481
t-stat	3.190	-0.908	2.951	3.361	-8.485		

Cohort 2

	Int	Rm-Rf	SMB	HML	RMW	CMA	R^2
Rm-Rf							
Coef	0.008		0.274	0.021	-0.355	-0.086	0.200
t-stat	2.187		2.880	0.189	-1.983	-0.451	
SMB							
Coef	-0.008	0.602		-0.127	0.775	0.596	0.295
t-stat	-1.514	2.880		-0.767	3.099	2.216	
HML							
Coef	-0.002	0.040	-0.109		0.331	0.417	0.068
t-stat	-0.427	0.189	-0.767		1.317	1.639	
RMW							
Coef	0.007	-0.241	0.240	0.120		-0.516	0.363
t-stat	2.362	-1.983	3.099	1.317		-3.781	
CMA							
Coef	0.008	-0.056	0.176	0.144	-0.492		0.303
t-stat	3.036	-0.451	2.216	1.639	-3.781		

Source and representation: Own elaboration

In Cohort 1, the excess market return (Rm-Rf = EMR) shows a positive, significant intercept ($\alpha = 0.008$, $t = 4.12$). SMB's intercept is small and insignificant ($\alpha = -0.005$, $t = -1.57$). HML's intercept is also insignificant ($\alpha = -0.002$, $t = -0.69$). By contrast, RMW ($\alpha = 0.005$, $t = 2.86$) and CMA ($\alpha = 0.006$, $t = 3.19$) deliver statistically positive alphas. R^2 is highest when the dependent variable is RMW (0.49) or CMA (0.48), and lower for EMR, SMB, and HML (0.15 – 0.22). This means in early post-IPO years, profitability and investment are not spanned by the other four factors and carry independent pricing information – size and value do not.

In Cohort 2, EMR again has a positive, significant intercept ($\alpha = 0.0079$, $t = 2.19$). Both SMB's and HML's intercepts remain insignificant ($\alpha = -0.0084$, $t = -1.51$), ($\alpha = -0.0022$, $t = -0.43$). RMW ($\alpha = 0.0070$, $t = 2.36$) and CMA ($\alpha = 0.0085$, $t = 3.04$) continue to have positive, significant alphas. R^2 falls relative to Cohort 1 for RMW (0.36) and CMA (0.30), is a bit higher for EMR (0.20) and SMB (0.29), and is very low for HML (0.07). Profitability and investment still are not spanned – size and value remain redundant on average.

Several patterns shift from Cohort 1 to Cohort 2. The intercepts for profitability and investment rise with firm age. For RMW, alpha rises from 0.005 to 0.007 (t: 2.86 → 2.36) and for CMA, alpha rises from 0.006 to 0.0085 (t: 3.19 → 3.04), while both alphas remain statistically significant. The higher alphas imply that, for older IPOs, the profitability and investment factors contain more independent pricing information that is not captured by the other four factors as firms mature.

At the same time, the spanning R^2 falls for these two factors (RMW: 0.49 → 0.36; CMA: 0.48 → 0.30). This suggests their variation is less replicable by the other factors, consistent with the correlation matrix becoming more orthogonal in Cohort 2.

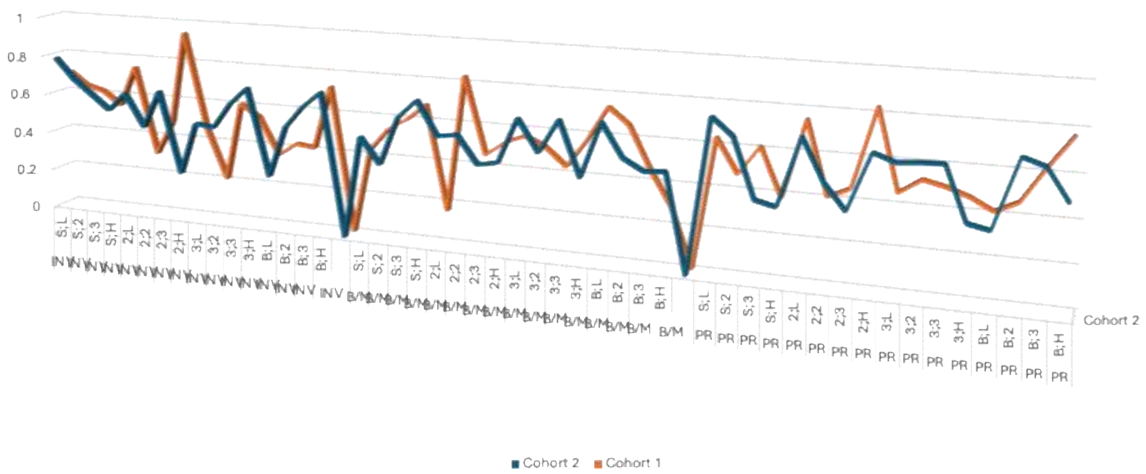
EMR remains broadly unchanged, while SMB and HML alphas stay insignificant.

These results indicate that, as IPO firms mature, the independent roles of profitability and investment strengthen (higher alphas and less spanned variation). This points to clearer, more interpretable factor exposures in later years and supports the expectation that the FF5 model will explain IPO returns better for Cohort 2 than for Cohort 1.

3.4.4 Time Series Regression

In the final step, the time-series regressions for each of the 48 equal-weighted test portfolios are conducted separately for both cohorts. Monthly excess returns are regressed on the five Fama–French factors as constructed in Section 3.2. First, I compare the adjusted R^2 values of the two cohorts, as shown in the graph below. The adjusted R^2 shows how much of the monthly excess-return variation the factors can explain and accounts for the number of factors used. Higher values mean the model fits the data better.

Figure 5: Adjusted R^2 for 48 regressions across both cohorts



Source and representation: Own elaboration

Inspecting the figure shows no large gaps in adjusted R^2 across the two 48 regressions. To summarize the pattern, I average adjusted R^2 for the three size-characteristic blocks. The mean adjusted R^2 increases from Cohort 1 to Cohort 2: from 0.5427 to 0.5692 for Size × Investment, from 0.5270 to 0.5434 for Size × B/M, and from 0.5466 to 0.5517 for Size × Profitability. The corresponding gains are + 0.0265, + 0.0163, and + 0.0051. These increases are modest but consistent. Thus, the five-factor model explains returns slightly better for firms in years 6 – 10 than in years 2 – 6. This suggests that, in later years, there is less random noise in returns, and the effect of the factors is clearer. This evidence supports Hypothesis 1.

After this macro comparison of the two cohorts, we now go one step deeper and take a more micro-level look at how the factor sensitivities (betas) evolve as IPO firms mature. The intercept (α) captures the average abnormal return not explained by these five factors. The coefficients (betas) measure how strongly each portfolio co-moves with the systematic risk factors, while their statistical significance indicates which effects are robust across firm groups. The tables report portfolio betas with respect to each factor across all 4×4 test portfolios for both cohorts. All bold values with an asterisk (*) are statistically significant at the 5% level ($|t| > 1.96 \approx p < 0.05$).

Table 4: CMA Beta Estimates for 20 Equal-Weighted Size–INV, Size–B/M, and Size–PROF Portfolios (Cohort 1 and Cohort 2)

	Cohort 1				Cohort 2			
CMA|	Low	2	3	High	Low	2	3	High
	INV				INV			
Small	0.2532	0.2315	-0.3567	**-1.0495***	0.3513	-0.0367	0.0789	**-1.2639***
2	**1.9079***	0.4886	0.1223	**-2.5693***	**1.3623***	0.5095	**-0.532***	**-2.8349***
3	0.0322	0.2037	-0.2059	0.0867	0.9796	-0.0331	-0.0948	-0.5112
BIG	0.4666	0.3154	0.3198	-0.3122	0.4755	**0.7823***	-0.0464	-0.1931
	B/M				B/M			
Small	-0.9504	-0.5388	**0.9327***	-0.1759	-0.7656	-0.4316	0.9301	-0.0072
2	-0.5377	1.4924	0.015	0.0152	0.7536	0.7196	-0.0357	-0.1071
3	0.1991	0.1301	-0.2201	-0.0105	-0.1777	-0.0567	0.2049	0.1451
BIG	0.1375	-0.0182	0.1877	0.5443	-0.1259	0.0964	0.6071	0.9715
	PROF				PROF			
Small	-0.497	-0.1321	-0.1605	**1.0946***	0.3167	-0.0571	-0.5353	-0.9545
2	**2.3952***	0.0669	-0.2223	**-1.2495***	-0.311	**0.9199***	-0.0981	0.8362
3	-0.5189	-0.1505	0.3366	0.2563	0.3056	-0.698	0.4923	-0.0175
BIG	0.2159	-0.3055	0.3383	**0.3955***	-0.4548	0.1567	-0.0379	0.1554

Source and representation: Own elaboration

Overall, there are no consistent or systematic patterns in the betas across size or characteristic groups, and most coefficients are not statistically significant at conventional levels.

As shown in Table 4, significance for the CMA factor appears only sporadically, and the signs and magnitudes vary without a clear pattern either within or across cohorts. The only visible tendency among the significant CMA loadings in the Size × Investment test portfolios is that portfolios with higher investment intensity tend to exhibit more negative CMA betas. This is economically intuitive, as firms with higher investment levels generally earn lower stock returns. Therefore, H_2-e is not supported by evidence.

Table 5: RMW Beta Estimates for 20 Equal-Weighted Size–INV, Size–B/M, and Size–PROF Portfolios (Cohort 1 and Cohort 2)

	Cohort 1				Cohort 2			
RMW|	Low	2	3	High	Low	2	3	High
	INV				INV			
Small	-0.0203	-0.0586	-0.3908	**-1.0081***	**-1.2464***	0.218	**1.1553***	-0.1134
2	0.3553	**0.5412***	0.0625	**2.5633***	-0.0136	0.573	-0.3341	**-2.0591***
3	0.501	0.4966	0.0702	0.2935	-0.2746	-0.0878	0.0401	**-0.7757***
BIG	**0.7976***	**0.5796***	0.5484	0.0311	0.2832	0.3289	-0.1436	0.0267
	B/M				B/M			
Small	**-1.4581***	-0.5798	0.7239	-0.2351	0.6664	-1.3278	0.0891	**-0.4314***
2	-0.4283	**2.9448***	0.1771	0.2408	0.795	**-1.1506***	-0.0325	-0.3289
3	0.1236	**0.4864***	0.3517	0.4128	-0.2869	-0.1065	**-0.6631***	0.1787
BIG	0.253	0.3854	0.5799	**0.947***	-0.0675	-0.0366	**0.8222***	0.0238
	PROF				PROF			
Small	-0.8412	-0.2576	-0.4134	**1.2448***	**-0.9952***	-0.3364	-0.0266	0.3784
2	-0.1153	0.1094	0.0898	**3.7631***	**-1.6792***	-0.2781	0.4413	**1.9897***
3	-0.1024	0.0153	**0.6848***	**0.599***	-0.0965	**-1.7586***	0.068	0.445
BIG	0.4317	-0.1406	**0.75***	**0.7559***	0.7807	-0.2803	**-0.5052***	0.2547

Source and representation: Own elaboration

For the RMW factor, a similar picture emerges – as demonstrated in Table 5. While a few coefficients reach statistical significance, there is no systematic difference between Cohort 1 and Cohort 2. The signs of the RMW betas also change randomly within test portfolios and across cohorts. This indicates unstable profitability exposures among IPOs. Hence, there is no evidence to support H_2-d.

Table 6: HML Beta Estimates for 20 Equal-Weighted Size–INV, Size–B/M, and Size–PROF Portfolios (Cohort 1 and Cohort 2)

	Cohort 1				Cohort 2			
HML|	Low	2	3	High	Low	2	3	High
	INV				INV			
Small	0.3474	**0.4918***	**0.4219***	**0.7026***	**0.4491***	**0.2506***	-0.0946	**-0.7338***
2	**-1.9038***	-0.1888	-0.0552	**-2.0343***	**-0.9547***	-0.2344	**0.4326***	-0.2532
3	**-0.5566***	-0.073	**-0.2794***	**-0.4807***	-0.1661	**0.2845***	-0.0454	-0.0737
BIG	**-0.7239***	**-0.472***	**-0.4669***	**-0.4853***	-0.259	**-0.3455***	**-0.3845***	**-0.3149***
	B/M				B/M			
Small	0.3969	0.4247	0.1634	**0.5394***	**-0.9362***	-0.9228	**0.7888***	**0.3032***
2	-0.0374	**-4.6655***	-0.1723	**0.4014***	**-1.1751***	**-1.2626***	0.1627	**0.5825***
3	**-0.7758***	**-0.5658***	0.0917	-0.0051	**-0.5411***	-0.1973	**0.4792***	0.3343
BIG	**-0.7147***	**-0.6172***	-0.2679	-0.3398	**-0.5261***	-0.1067	**-0.4272***	-0.3514
	PROF				PROF			
Small	**0.6049***	**0.3654***	0.2585	0.4953	0.3373	**0.4787***	-0.4379	-0.5282
2	**-2.541***	-0.1882	-0.1215	**-2.0838***	**-0.8338***	0.0245	-0.0364	0.0679
3	**-0.4174***	**-0.31***	**-0.3869***	-0.3014	**-0.6656***	0.2639	**0.3653***	-0.026
BIG	**-0.8198***	**-0.5678***	**-0.5991***	**-0.3228***	-0.2647	**-0.5716***	**-0.5559***	-0.1467

Source and representation: Own elaboration

For the HML factor, exposures are more often statistically significant in Cohort 1. A very interesting finding is that in both Cohorts, especially small Caps, behave like value stocks with positive loadings. In contrast, large-cap portfolios in both cohorts load negatively, consistent with growth stock behaviour. Economically, this can be justified by the fact that small firms often trade at comparatively lower valuations, whereas large firms typically enter the market with high growth expectations and therefore exhibit low book-to-market ratios. However, no clear distinction is visible between the two cohorts, and therefore, there is no evidence to support H_2-c.

Table 7: Rm-Rf Beta Estimates for 20 Equal-Weighted Size–INV, Size–B/M, and Size–PROF Portfolios (Cohort 1 and Cohort 2)

	Cohort 1				Cohort 2			
Rm-Rf|	Low	2	3	High	Low	2	3	High
	INV				INV			
Small	**1.5545***	**1.03***	**0.9705***	**1.3048***	**1.5811***	**0.8715***	**1.3182***	**1.9861***
2	**0.8862***	**0.8397***	**1.2463***	0.5057	**1.1984***	**1.326***	**1.4635***	1.2825
3	**1.3107***	**0.6176***	**1.0627***	**1.3015***	**2.6654***	**1.0816***	**1.163***	**1.5398***
BIG	**1.0958***	**0.9147***	**0.7879***	**1.3829***	**1.4157***	**1.4849***	**1.0873***	**1.1835***
	B/M				B/M			
Small	**1.7052***	**1.6568***	**1.4662***	**0.9025***	**1.6226***	**2.4692***	**2.1871***	**0.8719***
2	**0.9064***	0.2957	**1.2978***	**1.0938***	**1.8433***	**1.128***	**1.1644***	**1.5768***
3	**1.3556***	**1.0758***	**0.7882***	**1.1443***	**2.0161***	**1.2314***	**1.4966***	**1.6402***
BIG	**1.1489***	**1.3547***	**0.8966***	**0.8863***	**1.1841***	**1.1703***	**1.6499***	**1.199***
	PROF				PROF			
Small	**1.6321***	**0.8573***	**1.0245***	**1.4506***	**1.8426***	**0.4976***	**1.4965***	**2.2156***
2	0.8702	**1.1888***	**1.3145***	0.1027	**1.308***	**1.4482***	**1.0468***	**2.0775***
3	**1.141***	**0.9961***	**1.0689***	**1.1547***	**2.1825***	**1.2896***	**1.659***	**1.0329***
BIG	**1.3763***	**0.8694***	**1.2223***	**1.0823***	**1.2389***	**1.6724***	**1.3315***	**1.005***

Source and representation: Own elaboration

For the EMR factor, almost all portfolios show positive and statistically significant betas in both cohorts. The coefficients are slightly higher on average and more often statistically significant in Cohort 2. This means that IPO returns move closely with the overall market and that market sensitivity even strengthens as firms mature. Economically, this can be justified by the decline in idiosyncratic uncertainty and the gradual integration of newly listed firms into the market, which increases their exposure to systematic risk over time. This pattern is fully consistent with the findings discussed in the literature review, particularly Chincarini et al. (2020), who document that IPO betas converge toward one as firms age. Hence, H_2-a is accepted.

Table 8: SMB Beta Estimates for 20 Equal-Weighted Size–INV, Size–B/M, and Size–PROF Portfolios (Cohort 1 and Cohort 2)

	Cohort 1				Cohort 2			
SMB	Low	2	3	High	Low	2	3	High
	INV				INV			
Small	**0.5931***	**0.5938***	**0.4519***	**0.8049***	**0.5418***	**0.5046***	**0.8055***	**0.998***
2	**0.7211***	-0.0984	-0.1883	**1.2424***	**0.5588***	0.1078	0.1489	0.0172
3	**-0.5505***	-0.1674	**-0.46***	**-0.4689***	**-1.1499***	**-0.5587***	**-0.3751***	**-0.6688***
BIG	**-0.5927***	**-0.5804***	**-0.6264***	**-0.7295***	**-0.652***	**-0.731***	**-0.5673***	**-0.6341***
	B/M				B/M			
Small	**0.6719***	**0.4797***	**0.5952***	**0.5238***	-0.254	**1.1532***	**0.7712***	**0.5858***
2	0.2545	**1.531***	0.0388	0.0507	0.4386	**0.6087***	0.1027	-0.0863
3	**-0.8041***	**-0.3938***	-0.1592	**-0.2169***	**-1.0633***	**-0.5683***	**-0.4266***	**-0.4613***
BIG	**-0.8128***	**-0.5922***	**-0.5835***	**-0.3794***	**-0.8171***	**-0.4085***	**-0.6175***	**-0.8987***
	PROF				PROF			
Small	**0.8159***	**0.4486***	**0.3037***	**0.6896***	**0.7065***	**0.7284***	**0.5074***	0.0083
2	**1.0903***	-0.0481	-0.1526	**1.12***	**0.6671***	-0.253	0.1068	0.2883
3	**-0.5682***	**-0.3653***	**-0.3777***	**-0.3567***	**-1.1868***	-0.1254	**-0.8225***	**-0.4748***
BIG	**-0.7689***	**-0.7904***	**-0.6736***	**-0.4556***	**-1.1154***	**-1.0851***	**-0.5637***	**-0.3867***

Source and representation: Own elaboration

For the SMB factor, many betas are statistically significant, especially for the smallest and largest portfolios. Small-cap portfolios load positively and significantly on SMB, while large-cap portfolios show negative and significant loadings, consistent with the theoretical size effect. Results for the mid-size portfolios are mixed and often insignificant, which is expected since these firms lie between the small- and large-cap extremes, where the size premium is less pronounced. The overall pattern is similar across both cohorts, with no systematic shift in factor loadings as firms mature. Consequently, there is no evidence that the size effect strengthens with firm age, which is why H_2-b is rejected.

Table 9: alpha Beta Estimates for 20 Equal-Weighted Size–INV, Size–B/M, and Size–PROF Portfolios (Cohort 1 and Cohort 2)

	Cohort 1				Cohort 2			
α|	Low	2	3	High	Low	2	3	High
	INV				INV			
Small	0.0106	**0.0206***	0.0092	0.0083	0.0045	-0.0004	-0.0091	-0.0193
2	-0.0062	0.0068	0.0013	-0.006	0.002	0.0007	-0.0044	0.0137
3	0.005	-0.0004	**0.0135***	0.0001	-0.0106	0.0064	0.004	0.0012
BIG	-0.0002	0.0068	0.0039	-0.0019	0.0029	-0.0067	0.0003	-0.0014
	B/M				B/M			
Small	0.0066	**0.0191***	**0.0157***	0.0017	0.0054	-0.0161	-0.0136	0.0032
2	0.0113	-0.0301	0.0085	0.0056	-0.0004	-0.0024	0.0018	-0.0007
3	**0.0204***	0.0031	-0.0006	-0.0018	-0.003	0.0036	0.0014	-0.0013
BIG	0.0007	**0.0112***	-0.0028	-0.0042	0.001	-0.0002	-0.0077	-0.0065
	PROF				PROF			
Small	**0.0175***	0.0065	0.0097	0.008	-0.0032	0.005	-0.0067	-0.005
2	-0.0192	0.0101	-0.0029	0.004	0.0019	0.0005	0.0064	-0.0106
3	0.012	0.004	0.0086	0.0008	-0.0051	0.0055	0.0002	0.0034
BIG	-0.0022	0.0037	-0.0005	0.0013	-0.0047	-0.0037	-0.0008	0.0007

Source and representation: Own elaboration

Across all 4×4 test portfolios and both event-time cohorts, the estimated intercepts (alphas) are, with few exceptions, statistically insignificant. In the framework of the Fama–French FF5 model, alpha represents the average abnormal return unexplained by systematic risk factors. Insignificant alphas therefore suggest that, once these risk premia are controlled for, there is little evidence of abnormal performance in the portfolio returns.

A closer inspection reveals that a few alphas in Cohort 1 are weakly significant at the 5% level, whereas all alphas in Cohort 2 are statistically insignificant. While individual alpha significance should be interpreted with caution — given potential multiple-testing effects and the limited statistical power in small samples — the general pattern is consistent with a decline in idiosyncratic influences as firms mature.

Together with the observed increase in adjusted R^2 values across cohorts, these results indicate that the explanatory power of the Fama–French five-factor model improves with firm age. This development suggests that, over time, IPO firms' return dynamics become more strongly driven by systematic market and style factors. This reflects reduced firm-specific noise and more stable risk exposures.

3.4.5 Summary of Results

Overall, the evidence shows a modest but consistent improvement in model fit as IPO firms mature. Factor correlations decline from Cohort 1 to Cohort 2. Especially, profitability and investment indicate a more orthogonal factor structure and stronger factor independence in later years. This pattern is confirmed by the factor spanning tests, which show that the EMR, RMW, and CMA factors carry independent pricing information in both cohorts, while the independent pricing contribution of RMW and CMA increases from Cohort 1 to Cohort 2. The market factor remains unchanged, and SMB and HML are largely redundant on average. The average adjusted R^2 of the 48 time-series regressions is slightly higher in Cohort 2 and varies less across portfolios, suggesting a more stable specification as firms age. Overall, a larger share of return variance is explained in Cohort 2 than in Cohort 1.

In terms of factor loadings, market betas are positive and broadly significant. They are higher on average in Cohort 2, consistent with stronger market integration and less idiosyncratic risk of IPO firms over time. SMB behaves as expected at the extremes. Small portfolios load positively and large portfolios negatively, while mid-size portfolios are mixed and often insignificant. But there is no systematic shift in size exposure across cohorts. In Cohort 1, the value factor (HML) matters more often. In this cohort, small firms tend to behave more like value stocks, while large firms tend to behave more like growth stocks. This pattern does not strengthen with firm age. RMW and CMA loadings are mostly unchanged, not significant across cohorts, and show no systematic trend. Intercepts are generally insignificant. Together with the rise in adjusted R^2, this pattern indicates that the five-factor model explains IPO returns slightly better in later post-listing years, likely due to clearer factor structure and stronger market co-movement rather than larger non-market exposures. Overall, a substantial share of the estimated effects is not statistically significant, so the hypothesis tests with the outcome “not supported by evidence” should be viewed as indicative rather than definitive. The results of these tests are summarized in Table 10.

Table 10: Summary of Hypothesis Test Results

Hypothesis	Description	Outcome
H1	Model fit improves with firm age	Accepted
H2-a	Market beta increases with firm age	Accepted
H2-b	Size loading strengthens with firm age	Rejected
H2-c	Value loading strengthens with firm age	Not supported by evidence
H2-d	Profitability loading strengthens with firm age	Not supported by evidence
H2-e	Investment loading strengthens with firm age	Not supported by evidence

Source and representation: Own elaboration

4. Conclusion

Motivated by the strong growth of global equity markets, the rise of factor investing as a key tool for harvesting equity risk premia, and the close link between factor products and academic asset-pricing models, this thesis extends the analysis of factor models to a largely underexplored niche: newly listed firms. While IPO performance and factor models have both been examined extensively in isolation, comparatively little is known about how the explanatory power and factor structure of factor models evolve over a firm’s post-IPO life. To address this gap, the thesis posed the central research question: Does the Fama–French five-factor model explain stock returns of IPO firms better in their later post-IPO years than in their early post-IPO years? A two-step analysis is conducted, beginning with the literature review, which first traces the development from CAPM to the Fama–French five-factor framework, highlighting how market, size, value, profitability, and investment characteristics are linked to expected returns, and showing the relevance of the five-factor model. It then summarized empirical evidence on IPO firms, emphasizing their high initial idiosyncratic risk, lower profitability, higher investment, and muted size and value signals in early years, as well as the gradual convergence of betas and risk premia toward those of seasoned firms. Together, these strands suggest that the relevance of factors regarding IPOs is likely to change over time and that firm age may matter for the performance of multi-factor models.

Empirically, the thesis used monthly data on US IPOs listed on Nasdaq, AMEX, and NYSE between 1990 and 2020. Firms were followed over their first decade on the market and grouped into two event-time cohorts. Firms are pooled by IPO age rather than calendar year. All IPOs that are 2–6 years past listing are grouped into Cohort 1, and those 6–10 years past listing into Cohort 2, regardless of their actual listing date. This pooling by time since IPO allows the analysis to examine how factor exposure and the explanatory power of the FF5 model evolve as firms mature. Following the Fama and French (2015) approach, I construct characteristic-sorted portfolios based on size and profitability, as well as investment and book-to-market (B/M). The factor-mimicking portfolios are built from independently sorted 2×2 portfolios on size and each characteristic, using the sample median as the breakpoint and equal weights within each cell. The test portfolios are formed using an independent, 4×4 equal-weighted procedure based on the same characteristics, with portfolios defined using quartile breakpoints. The empirical analysis combines factor summary statistics, correlation matrices, and factor-spanning tests. Then, time-series regressions of portfolio excess returns were estimated using the five FF5 factors, with 48 monthly observations (4-year window) for each cohort. Time-fixed effects are included in the regression specification to control for standard period-specific shocks, enabling a more precise evaluation of the hypotheses on model fit and the evolution of factor loadings with firm age. The results show a modest but consistent improvement in model fit from Cohort 1 to Cohort 2. Correlation tests show that factor co-movements weaken as firms mature, indicating a more orthogonal and cleaner factor structure in Cohort 2. Spanning tests suggest that the independent pricing information contained in the profitability (RMW) and investment (CMA) factors increases from Cohort 1 to Cohort 2. In the time-series regressions, adjusted R^2 is marginally higher and less dispersed across portfolios in Cohort 2, suggesting a slightly better, more stable fit of the FF5 model in later post-IPO years. The beta estimates reveal consistently positive and sizeable market exposure in both cohorts. In contrast, loadings on SMB, HML, RMW, and CMA are often unstable and provide limited evidence of systematically stronger sensitivities as firms mature.

Overall, the evidence offers tentative support for the view that the FF5 model explains IPO returns somewhat better as firms season. This improvement appears to be driven more by a gradual stabilization of factor structures and stronger co-movement with systematic risks than by sharply increasing non-market factor exposures. However, several coefficients are imprecisely estimated, and some results are not statistically significant, so these conclusions are rather indicative than definitive.

This article is subject to several limitations, including sample selection. Only IPOs that survive at least ten years are retained, and firms with a market capitalization below USD 100 million at $t = 2$ are excluded. These filters remove very small issuers and all firms that fail within the first decade. That can bias estimates, factor loadings, and average portfolio returns. Furthermore, the number of IPO firms is limited, and it is difficult to expand the set of observed companies substantially. Extending the analysis beyond the domestic market can increase the sample size but may introduce additional imbalances. A further limitation concerns calendar timing. Cohort 1 and Cohort 2 fall into different macro periods. Because IPO activity collapsed, as shown in Figure 2, in 2001–2003 and again in 2008–2009, the resulting sample exhibits cohort imbalances. For example, relatively few firms went public in 2001–2003, so listings from these years contribute only a small number of observations to Cohort 1 from 2003-2007. Furthermore, the limited number of observations (48) within each cohort is the main reason for the many insignificant estimates and for the inability to evaluate three hypotheses, as statistical significance cannot be established.

Overall, it is important to keep these limitations in mind when analysing the results. The findings apply to US IPOs that survive for 10 years, across short 4-year windows, using one FF5 setup and fixed portfolio sorts. Calendar periods (e.g., the dotcom bust, the Global Financial Crisis) and sample filters (survivorship, size) can influence estimates of factor premia, betas, and alphas. The short time span might reduce statistical precision. These issues don’t invalidate the patterns I find, but they mean the conclusions should be viewed as context-specific rather than broadly universal.

Future work can deepen and broaden these findings. A first step is to raise the time-series density by using weekly (or daily) returns. The sample could also be expanded to include micro- and nano-caps by relaxing the USD 100m screen and adding delisting returns. This would significantly increase the number of observations within each cohort, improving statistical precision and making the alpha and beta estimates more reliable. Furthermore, an increase in observations would enable conducting a GRS test, as in Fama and French, which could help identify differences in the factors' predictive power. Additionally, the Model design can be varied in several ways. Repeating the analysis using alternative breakpoints and portfolio-sorting schemes (such as 2×3 or 2×2×2×2) for both the factor-mimicking portfolios and the test portfolios would allow testing the robustness of the main conclusions and yield clearer or more significant results. Moreover, adding a momentum and/or a liquidity factor to the FF5 baseline might improve the model's explanatory power. Momentum may be relevant for newly listed firms, as IPOs often show short-term trends after listing. Considering liquidity can be important, since younger, and hence often smaller, firms tend to trade at lower volumes and with wider bid–ask spreads, so an illiquidity premium may show up in returns. Finally, using alternative accounting measures of profitability and investment (e.g., gross profitability, operating ROA, asset or book-equity growth) would enhance measurement robustness and could potentially lead to a better model fit.

Additionally, a change in methodology could involve estimating rolling-window betas to examine how factor exposures evolve over time. Estimating the FF5 regression on ,for example, overlapping 36-month windows by using returns and factors from months 1 – 36 and storing the betas. Then shifting the window by one month to 2 – 37, then 3 – 38, and so on. This procedure yields a monthly time series of betas (and alphas) for each IPO portfolio and can be continued as long as sufficient history is available. In the end, a concrete trend in the betas might be observed, which shows whether loadings on EMR, SMB, HML, RMW, and CMA rise or fall as firms mature. By overlaying simple macro states, the analysis can better distinguish maturity effects from business-cycle effects. Additionally, the overlapping windows make the results less sensitive to any specific month.

In sum, these extensions would test whether the main results are robust to more data, alternative designs, and changing market conditions. They would also show how general the findings are beyond the current sample and whether the signals are usable after real-world frictions.

References

Abhishek Gupta, S. D., 2025. *Factor Indexing Through the Decades.* [Online]
Available at: https://www.msci.com/downloads/web/msci-com/research-and-insights/paper/factor-indexing-through-the-decades/factor-indexing-through-the-decades.pdf
[Zugriff am October 2025].

Advisors, D. F., 2025. *Bloomberg's "Odd Lots": Eugene Fama and David Booth on the Birth of Modern Finance.* [Online]
Available at: https://www.dimensional.com/us-en/newsroom/odd-lots-eugene-fama-and-david-booth-on-the-birth-of-modern-finance#:~:text=Eugene%20Fama%20is%20a%20member,performance%20may%20not%20be%20repeated.
[Zugriff am september 2025].

Advisors, V. F., 2025. *Institutional Vanguard.* [Online]
Available at: https://institutional.vanguard.com/investments/product-details/fund/0006?utm_source=
[Zugriff am september 2025].

Bank, M. & Insam, F., 2021. Corporate aging and changes in the pricing of stock characteristics. *Finance Research Letters*, October.

Black, F., Jensen, M. C. & Scholes, M., 1972. The Capital Asset Pricing Model: Some Empirical Tests. *Studies in the Theory of Capital Markets*.

Blackrock, 2025. *Blackrock.* [Online]
Available at: https://www.blackrock.com/us/financial-professionals/products/239708/ishares-russell-1000-value-etf
[Zugriff am september 2025].

Brav, A., Geczy, C. & Gompers, P. A., 1998. Is the Abnormal Return Following Equity Issuances Anomalous?. *Journal of Financial Economics*, December, pp. 209-249.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance*, March, pp. 57-81.

Chincarini, L. B., Kim, D. & Moneta, F., 2020. Beta and Firm Age. *Journal of Empirical Finance*, pp. 50-74.

Claessens, S. & Laeven, L., 2005. Financial Dependence, Banking Sector Competition, and Economic Growth. *World Bank*, January, pp. 1-48.

Daniel, K. & Titman, S., 1997. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. *The Journal of Finance*, March, pp. 1-33.

Davis, J. L., Fama, E. F. & French, K. R., 2000. Characteristics, Covariances, and Average Returns: 1929 to 1997. *The Journal of Finance*, February, pp. 389-406.

Demirgüci-Kunt, A. & Levine, R., 1996. Stock Markets, Corporate Finance, and Economic Growth: An Overview. *The World Bank Economic Review*, pp. 223-239.

Fama, E. F. & French, K., 1992. The Cross-Section of Expected Stock Returns. *The Journal of Finance*, June, pp. 427 - 465.

Fama, E. F. & French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, September, pp. 3-56.

Fama, E. F. & French, K. R., 2004. The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives*, pp. 25-46.
Fama, E. F. & French, K. R., 2004. The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives*, pp. 25-46.
Fama, E. F. & French, K. R., 2008. Dissecting Anomalies. *The Journal of Finance*, August, pp. 1653-1654.

Fama, E. F. & French, K. R., 2012. Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 03 September, pp. 457-472.

Fama, E. F. & French, K. R., 2015. A five-factor asset pricing model. *Journal of Financial Economics*, October, pp. 1-3.

Fama, E. F. & MacBeth, J. D., 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, May - June, pp. 607-636.

Griffin, J. M., 2002. Are the Fama and French Factors Global or Country Specific?. *The Review of Financial Stdueis*, pp. 783-803.

Huberman, G. & Kandel, S., 1987. Mean-Variance Spanning. *The Journal of Finance*, September, pp. 873-888.

Jain, B. A. & Kini, O., 1994. The Post-Issue Operating Performance of IPO Firms. *The Journal of Finance*, December, pp. 1699-1726.

Lintner, J., 1965. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, February, pp. 13-37.

Loughran, T. & Ritter, J. R., 1995. The New Issues Puzzle. *The Journal of Finance*, March, pp. 23-51.

Markowitz, H. M., 1959. *Portfolio Selection: Efficient Diversification of Investments.* London: s.n.

Miller, M. H. & Modigliani, F., 1961. Dividend Policy, Growth, and the Valuation of Shares. *The Journal of Business*, October, pp. 411-433.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics*, 26 April, pp. 1-28.

Ritter, J. R., 2025. Initial Public Offerings: Updated Statistics. *The Journal of Finance*, April.

Sharpe, W. F., 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, September, pp. 426-442.

Sharpe, W. F., 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, September, pp. 425-442.

Stanford University, 2025. *Database Guide: WRDS: Identifiers and Linking Files.* [Online]
Available at: https://libguides.stanford.edu/library/wrds/identifiers-linking/files
[Zugriff am june 2025].

Szikszai, M. & Keith , C., 2024. *Sizing Up the Global-Market Portfolio.* [Online]
Available at: https://www.msci.com/research-and-insights/blog-post/sizing-up-the-global-market-portfolio
[Zugriff am October 2025].

Titman, S., Wei, K. J. & Xie, F., 2003. Capital Investments and Stock Returns. *NBER Working Paper series*, September, pp. 1-33.

Veronesi, L. P. P., 2002. STOCK VALUATION AND LEARNING ABOUT PROFITABILITY. *NATIONAL BUREAU OF ECONOMIC RESEARCH*, June, pp. 1-47.

Williams, J. B., 1938. *The Theory of Investment Value.* Cambride: Harvard University Press.

World Federation of Exchanges database, W. F. o. E. (. W.)., 2025. *World Bank Group.* [Online]
Available at: https://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS
[Zugriff am september 2025].

Appendix

Figure 1: Market capitalization of listed companies (% of GDP)

Source and representation: (World Federation of Exchanges database, 2025)

Table 1: average returns, STD Dev, T-tests of mimicking portfolios

Cohort 1

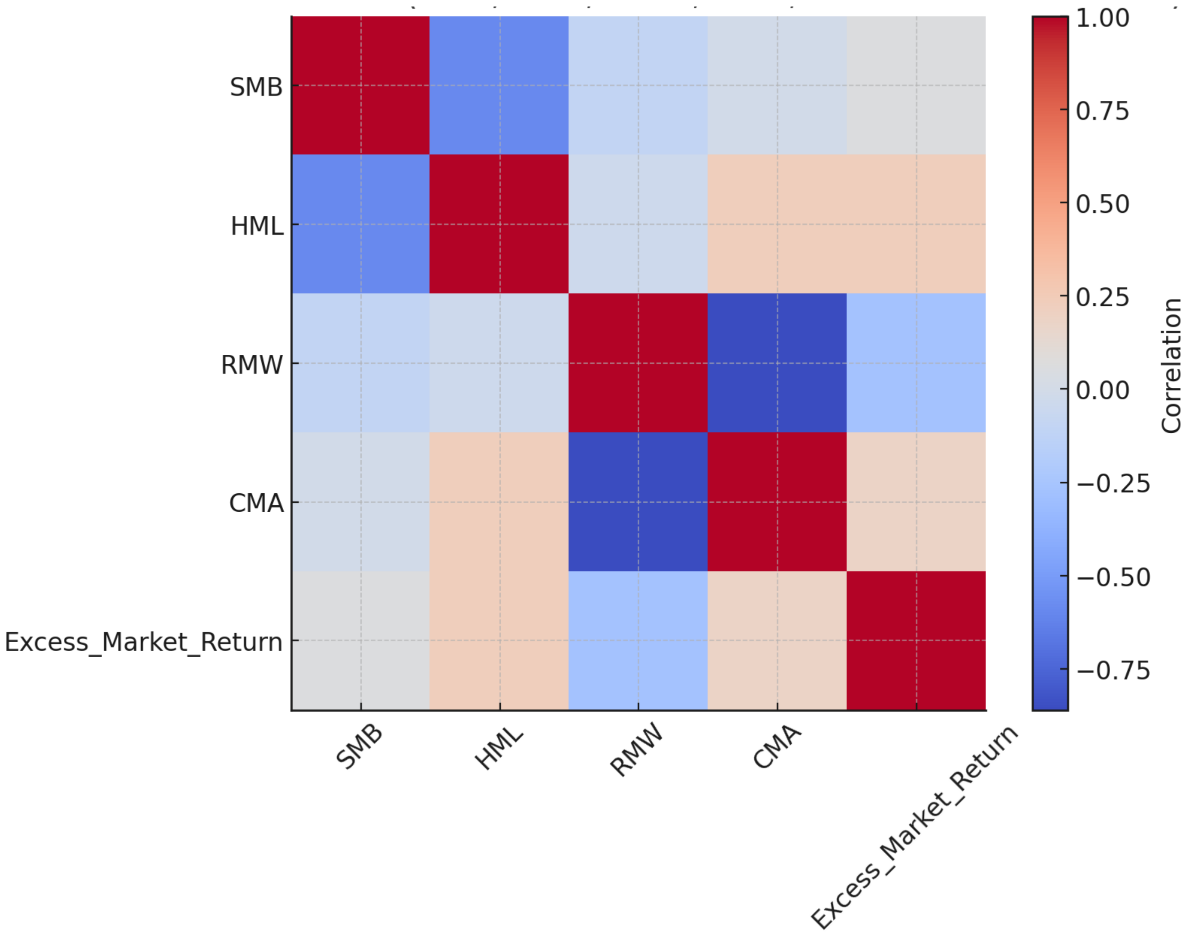
	SR	SW	SC	SA	SH	SL	BR	BW	BC	BA	BH	BL
Average	0.0114	0.0160	0.0166	0.0096	0.0184	0.0090	0.0148	0.0132	0.0142	0.0143	0.0122	0.0154
STD Dev.	0.0313	0.0297	0.0280	0.0385	0.0213	0.0403	0.0182	0.0185	0.0171	0.0195	0.0178	0.0195
T-test	2.5286	3.7355	4.1141	1.7300	5.9886	1.5500	5.6565	4.9497	5.7615	5.0674	4.7484	5.4531

Cohort 2

	SR	SW	SC	SA	SH	SL	BR	BW	BC	BA	BH	BL
Average	0.0179	0.0138	0.0199	0.0082	0.0157	0.0135	0.0125	0.0125	0.0146	0.0116	0.0136	0.0124
STD Dev.	0.0457	0.0463	0.0448	0.0454	0.0411	0.0580	0.0310	0.0452	0.0429	0.0338	0.0391	0.0362
T-test	2.7073	2.0658	3.0678	1.2581	2.6462	1.6093	2.7896	1.9160	2.3474	2.3735	2.4083	2.3680

Source and representation: Own elaboration

Figure 2: Correlation matrix between different factors



Source and representation: Own elaboration