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Factors-based Asset Pricing Models: a literature review

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Abstract

In this paper we provide a literature review of the main factors-based asset pricing models, focusing in particular on factors related to firm characteristics. After presenting the Capital Asset Pricing Model, we describe first the most important empirical evidence that led to the well-known Fama-French three-factors model. Next, we highlight the most widely used multi-factors pricing models based on momentum, liquidity, investment and profitability, also outside the U.S. Finally, we discuss the ability of firm characteristics to predict the behavior of future stock returns.

Keywords: *Asset Pricing, CAPM, Single-Factor and Multifactor Models, Anomalies*

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1. From the Capital Asset Pricing Model to Fama-French three-factors model

The first model of asset pricing proposed by finance scholars is the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). The CAPM builds on Markowitz (1952, 1959) mean-variance asset allocation model and states that, in equilibrium, the expected return of any security/portfolio *i*, $E(R_i)$, is equal to the risk-free rate, R_f, plus a risk-premium which is proportional to the risk premium of the market portfolio, $E(R_M) - R_f$, through a coefficient beta.

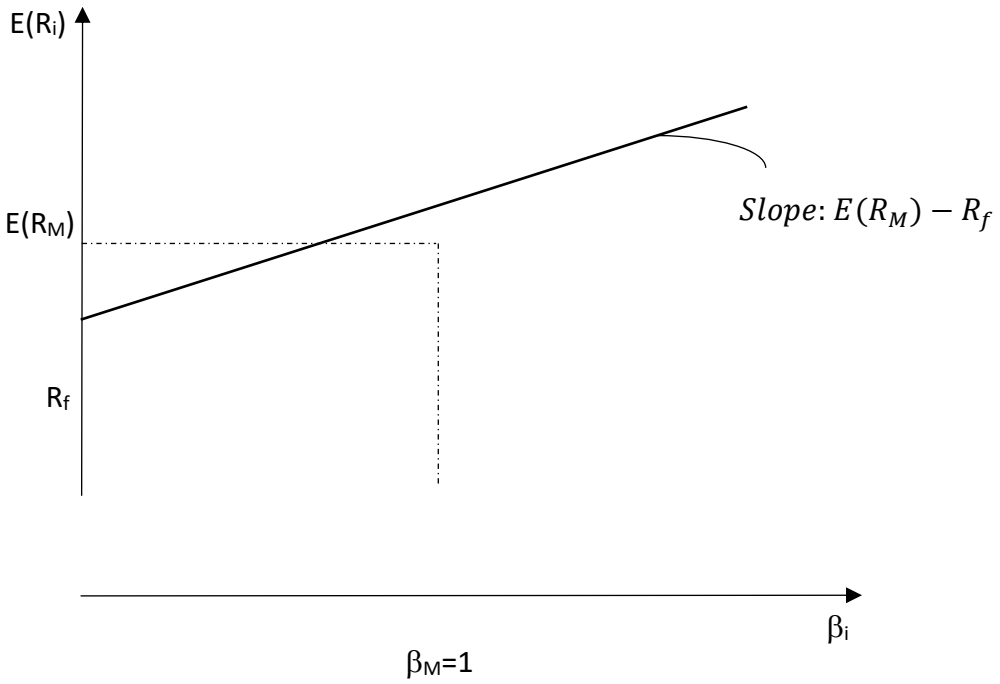
In formula,

$$E(R_i) = R_f + \beta_i * [E(R_M) - R_f]\,, \tag{1}$$

where $\beta_i = \frac{COV(R_i,R_M)}{VAR(R_M)}$.

Equation (1) is named Security Market Line (SML) and is depicted in Figure 1, in the expected return-beta space.

Figure 1. *Security Market Line*



According to the CAPM, the market portfolio represents the unique risk factor which affects the pricing of all securities. The cross-sectional variation in expected returns, instead, is due to the heterogenous sensitivity of each security return to the market portfolio return, that is the company β_i. In particular, the beta captures the part of risk that does not vanish with diversification, that is the systematic risk.

From Equation (1), it is easy to see that the market portfolio is characterized by a beta equal to 1. Therefore, $E(R_M) - R_f$ denotes the risk premium per unit of (systematic) risk. In equilibrium, all securities exhibiting the same beta as the market portfolio must provide the same expected return equal to $E(R_M)$. By contrast, securities with a beta less (more) than 1 bear a lower (higher) systematic risk and, hence, must offer an expected return lower (higher) than the one of the market portfolios.

The CAPM states that all assets lying on the SML are correctly priced whereas deviations from this line are due to mispricing.[1] Securities that are located above (below) the SML are under (over) priced since they offer an expected return higher (lower) than the one predicted by the model given the level of systematic risk. To better understand this point, recall the relationship between expected returns and prices: a higher expected return is equivalent to a higher discount rate, which in turn implies a lower discounted value of future cash flows, and hence a lower price.

Regarding its theoretical foundations, the Capital Asset Pricing Model hinges on the following set of assumptions:

- Investors have mean-variance preferences and choose the portfolio composition that maximizes their (expected) utility of next-period wealth. In particular, the mean-variance setting stems from either quadratic investor's utility function or jointly normally distributed returns.
- Investors exhibit homogeneous expectations about expected payoffs, risk, and correlations among assets.
- There are no transaction costs and taxes.
- It is possible to borrow and lend any amount of money at a constant risk-free rate.

Several scholars have often criticized the last assumption, casting doubts about its validity in the real world. In this regard, Black (1972) proposed an alternative version of the CAPM in which there exists no risk-free security. In particular, he shows that, when such an asset is not available, investors can still choose an efficient portfolio (located, however, on the Markowitz's efficient frontier). More importantly, the linear relationship between assets' expected returns and market expected returns proposed by Sharpe (1964) and Lintner (1965)

[1] In the latter case, arbitrage opportunities may arise. In turn, the resulting buying and selling pressure would affect the asset prices until equilibrium in financial markets is reached and the arbitrage opportunities vanish.

continues to hold, but with an important difference: the risk-free rate is replaced by the expected return of a portfolio characterized by zero covariance with the market portfolio.

Starting from the late '60s, many scholars have investigated the empirical validity of the CAPM. More precisely, using historical returns, they have estimated the following equation:[2]

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_i * [R_{M,t} - R_{f,t}] + \varepsilon_{i,t}, \quad (2)$$

where $R_{i,t}$ is the realized return of security *i* at time *t*, $R_{M,t}$ is the realized return of the market portfolio at time *t* and $\varepsilon_{i,t}$ is the error term. Equation (2) is also known as the *ex-post* form of the CAPM, in contrast to the *ex-ante* form of the Security Market Line reported in equation (1).

To mitigate the impact of measurement errors in betas that could arise from using individual securities data, equation (2) has often been estimated using portfolios returns, where portfolios are constructed by ranking stocks according to their past beta. The main advantage of this procedure is that it reduces the error-in-variables problem.

More importantly, if the CAPM correctly captures all the empirical variation in asset returns, the intercept α_i should not be statistically different from zero for all securities. Moreover, the inclusion of additional explanatory variables in equation (2) should not alter the results: the market factor must be the only relevant source of compensation for risk whereas the coefficients of the additional variables must be statistically indistinguishable from zero.

The most notable empirical tests of the CAPM have been conducted by Black, Scholes, and Jensen (1972) and Fama and MacBeth (1973). Specifically, using a time-series approach, Black, Scholes, and Jensen (1972) show that high beta (low beta) securities exhibit a significant negative (positive) intercept, which suggests that, in the data, average returns are not consistent with the predictions of the CAPM, thus leading to a rejection of the model. Fama and MacBeth (1973), instead, propose a new methodology to estimate the CAPM. They first estimate equation (2) using time-series regressions and then use the estimated betas of the securities as independent variable in cross-sectional regressions computed at each date. In particular, the estimated outcome of the cross-sectional regressions should coincide with the market risk premium. Moreover, they also show that their proxy for the market portfolio is the sole relevant source of risk.

More generally, the favorable results of the early tests of the CAPM contributed to create a consensus that such a model provided a reasonable description of asset returns.

[2] Recall that expected returns are not empirically observable and hence equation (1) is not testable. Therefore, testing the CAPM requires a "way" to replace expected returns with realized returns. The market model highlighted in equation (2) provides the solution.

Starting from late '70s, instead, a sequence of empirical studies challenged the validity of the CAPM. Several scholars, in fact, documented the existence of various variables related to average stock returns. For example, Banz (1981) shows that firms' market capitalization (hereafter size) is negatively related to equity returns: smaller firms earn on average higher risk-adjusted returns compared to large firms. In other words, size generates a statistically significant alpha, pointing out the existence of patterns in average stock returns that are considered anomalous because they are not explained by the CAPM. In this regard, the resulting size effect is one of the first documented evidence of deviations from the CAPM. Similarly, Basu (1983) proves that other fundamental characteristics are related to average stock returns. Specifically, stocks with high earnings-to-price ratio - *E/P* - earn on average higher returns compared to stocks with low *E/P* ratio. This result continues to hold even when controlling for size. Moreover, Bhandari (1988) finds that, controlling for market risk and size, the variable debt-to-equity ratio (which proxies leverage) is positively related to stock returns.

Similar results have also been found in other markets. For example, Chan, Hamao and Lakonishok (1991) show that book-to-market ratio (*B/M*) and cash-flow yield (*CF/P*) are positively related to average Japanese stock returns. By contrast, the performance of size highly depends on the time-period considered, whereas the earnings yield (*E/P*) effect disappears after controlling for other variables.

More generally, these results highlight that the market portfolio is not the sole variable able to explain stock returns.

Motivated by this evidence, Fama and French (1992) investigate the joint ability of the variables discussed so far, namely the book-to-market ratio, asset-to-equity ratio (which proxies leverage), earnings-to-price ratio, the market portfolio (hereafter *market*) and market capitalization, in explaining the cross-section of stock returns. Using a sample of NYSE, NASDAQ, and AMEX stocks over the period 1963-1990, they show that, controlling for size, *market* is not related to stock returns; moreover, when used alone, the variables book-to-market ratio, asset-to-equity ratio, and earnings-to-price ratio exhibit a significant explanatory power for the cross-section of average returns. By contrast, when combined with the other variables, size and book-to-market absorb the role of leverage and *E/P*.

According to Fama and French (1993), the fundamental variables related to stock returns must proxy for sensitivity to systematic risk factors, and thus they may be helpful in the construction of portfolios that mimic the properties of the risk factors, contributing to explain the cross-sectional variation in stock returns.

Based on this intuition, Fama and French (1993) propose a new asset pricing model characterized by three factors, namely the market portfolio risk premium, a factor proxying size (SMB), and one proxying the book-to-market ratio (HML).

Their procedure is based on the following steps. First, they sort all stocks according to their market capitalization and create two groups representing small and big stocks. Next, all securities are sorted again according to their book-to-market ratio and allocated to three groups

representing firms with low, medium, and high B/M. Then, for each intersection of size and book-to-market groups, the authors compute value-weighted portfolio returns. In this way, they obtain six portfolios. By computing the average return difference between the three portfolios of small stocks (small/low, small/medium, small/high) and the three portfolios of large stocks (large/low, large/medium, large/high), they obtain the factor *SML* (i.e., small minus big). Similarly, by computing the average return difference between the two portfolios of high (small/high, large/high) and two portfolios of low (small/low, large/low) book-to-market ratio stocks, they obtain the factor *HML* (i.e., high minus low).

In formula, they propose to estimate the following:

$$R_{i,t} - R_{f,t} = \beta_{i,M} * \left[R_{M,t} - R_{f,t}\right] + \beta_{i,SMB} * SMB_t + \beta_{i,HML} * HML_t + \varepsilon_{i,t}. \quad (3)$$

To investigate the validity of their three-factors model, Fama and French (1993) perform time-series regressions in which the dependent variables are the excess realized returns of quintile portfolios constructed by double sorting stocks on size and B/M[3], and, as robustness test, by univariate sorting stocks on earnings-to-price ratio and dividend-to-price ratio. Their results indicate that the three-factors model highlighted above captures quite well the variation in stock returns. This ability is not only limited to the stock market, but it is also present in the bond market; indeed, *SMB* and *HML* are also helpful in explaining variation in corporate and government bond portfolios, suggesting the existence of common risk factors.

2. Beyond the Fama-French three-factors model: evidence from firms' characteristics

The evidence documented by Fama and French (1992, 1993), and presented in the previous section, encouraged many scholars to search for additional factors able to explain the cross-section of expected stock returns.[4]

In a time-series analysis Jegadeesh and Titman (1993) find that stocks that have performed well in the past, that is past winners, tend to perform well in the future, especially over the 3-12 months horizon. Similarly, stocks that have not performed well in the past, that is past losers, keep continuing to perform poorly. They also show that zero-cost strategies consisting in buying past winners and selling past losers generate significant positive returns. This

[3] In this case the number of portfolios is 5 x 5 = 25.
[4] At the same time, the empirical methodology suggested by Fama and French (1993) to construct their factors has been used by the vast majority of scholars looking for additional sources of systematic risk.

phenomenon (i.e., the persistence of stock returns performances over time) was named *momentum effect* by the literature.

Interestingly, Fama and French (1996) show that their three-factors model was not able to capture the momentum effect in the cross-section of stock returns. Motivated by this inability, Carhart (1997) augmented the Fama-French three-factors model with the inclusion of a fourth factor, that is *WML*, which is computed as the average returns difference between past winners and past losers. Specifically, using monthly data from mutual funds returns, Carhart (1997) shows that the explanatory power of the resulting four-factors model, measured by the adjusted R^2, ranges between 89% and 97%.

Starting from the evidence of Jegadeesh and Titman (1993), finance scholars have shown that momentum returns have actually existed for 212 years, that is from 1801 to 2012 (Geczy and Samonov, 2013), are common to more than 40 countries (Rouwenhorst, 1998; Asness, Moskowitz and Pedersen, 2013) and to many asset classes (Asness et al. 2013), crash from time to time (Daniel and Moskowitz, 2016), and are driven by firm-specific attributes such as revenues, costs, and growth options (Sagi and Seasholes, 2007)[5].

From a theoretical point of view, Hong and Stein (1999) provide a model which can explain both the momentum and the long-term reversal effects. In their framework, the gradual diffusion of information among investors leads to stock price underreaction to new information, which, in turn, generates momentum in returns. By contrast, Daniel, Hirshleifer and Subrahmanyam (1998) develop a model featuring two psychological biases, that is overconfidence and self-attribution, to explain market overreaction to news. More recently, Vayanos and Woolley (2013) have shown how fund flows can generate both momentum and reversal.

Few years after the evidence documented by Carhart (1997), Pástor and Stambaugh (2003) showed that the CAPM, the Fama-French three-factors model, and the Carhart (1997) four-factors model generate significant alphas when used to explain the behavior of portfolios sorted on a proxy of liquidity. These results represented a further challenge to the pricing of stock returns and led the authors to search for a new pricing model. In this regard, they proposed an augmented Fama-French three-factors model with the inclusion of an additional factor capturing liquidity risk. Their results highlight that liquidity risk is a priced risk factor and stocks with high exposure to such a factor exhibit higher expected returns.

Another contribution highlighting the importance of liquidity in asset pricing is Acharya and Pedersen (2005). These authors propose a simple theoretical model of asset pricing to investigate how liquidity risk and commonality in liquidity affect security prices. Their empirical analysis shows that this liquidity-adjusted capital asset pricing model has a good fit in the case of portfolios sorted on liquidity, liquidity variation and size. By contrast, it cannot

[5] The literature has also documented the existence of a *reversal effect*, that is the tendency of past winners (losers) to become losers (winners) in the future, especially in long-term horizons.

explain the cross-sectional variation of returns associated with the book-to-market characteristic.

In the next years, the asset pricing literature has documented a growing number of variables related to average stock returns. For example, profitability has been found to be positively related to average stock returns (Cohen, Gompers, and Vuolteenaho, 2003; Novy-Marx, 2013). On the other hand, risk-of-failure (Campbell, Hilscher and Szilagyi, 2008), change in shares outstanding (Pontiff and Woodgate, 2006), and idiosyncratic volatility – that is exposure to innovation in aggregate market volatility (Ang, Hodrick, Xing, and Zhang, 2006) – are negatively related to stock returns.

Another strand of literature, instead, has investigated the pricing implications of higher moments of returns distribution, focusing in particular on third- and fourth-order moments. Specifically, Kraus and Litzenberger (1976), Friend and Westerfield (1980) and Sears and Wei (1985) extend the standard Capital Asset Pricing Model to encompass the effect of skewness on valuation and obtain mixed results. Harvey and Siddique (2000) propose a pricing model which incorporates conditional skewness. They find that conditional skewness helps explaining the cross-sectional variation of stock returns, controlling also for size and book-to-market factors.

More generally, the asset pricing literature has often used the word *anomaly* each time a new factor was discovered. Specifically, an asset pricing anomaly arises when the securities' realized returns are statistically different from the returns predicted by an asset pricing model, thus leading to a significant intercept alpha (Brennan and Xia, 2001). In this regard, it is important to notice that the alpha arising when using a specific model may disappear when considering another model. In other words, anomalies strongly depend on the choice of the asset pricing model.

Fama and French (2008) provide evidence against some of the conclusions found by the literature about the ability of several firms' characteristics in explaining stock returns. In particular, they show that the sample of firms analyzed matters, and that several anomalies arise because of a specific type of companies, namely the micro-cap firms. In this regard, they propose to divide the whole sample of securities in three groups based on their market capitalization, that is micro, small and big-cap. Interestingly, variables such as book-to-market, net stock issues, accruals and profitability exhibit a significant effect across all size groups. Momentum, instead, is stronger in micro-caps, and marginal in small and big-cap firms. Finally, size effect occurs in micro-cap stocks.

Regarding the evidence related to the variables capturing firms' investment and profitability, Haugen and Baker (1996) find that average stock returns are positively related to profitability whereas Titman, Wei, and Xie (2004) report a negative relationship between average stock returns and investment. In line with these results, Novy-Marx (2013) proposes a four-factors asset pricing model characterized by the market factor, an industry-adjusted value factor, an industry-adjusted momentum factor and an industry-adjusted profitability factor. Such a model

outperforms empirically the standard Fama-French three-factors model. Hou, Xue, and Zhang (2015) also propose a four-factors model that combines *market* and *size* factors with two new factors based on investment[6] and profitability[7]. The explanatory power of this model is higher than those of Fama-French three factors and Carhart four-factors models.

Fama and French (2015), instead, augment their well-known three-factors model with the inclusion of a somewhat different version of investment and profitability factors, thus creating a five-factors model based on the market factor, *SMB*, *HML*, *RMW* (i.e., robust minus weak) and *CMA* (i.e., conservative minus aggressive). Specifically, *RMW* is computed as the average returns difference between high and low operating profitability stocks, whereas *CMA* is computed as the average returns difference between high and low investment firms – measured as the relative change in total asset. This five-factors model does a good job in explaining the cross-section of returns for portfolios sorted on a combination of size, *B/M*, investment, and profitability, and outperforms their standard three-factors model. However, the model performs poorly when pricing small firms characterized by low profitability and sustained investments.

As explained in the previous section, the typical approach followed by the literature to identify a potential explanatory variable consists first in sorting all stocks according to the realization of that variable, then in assigning each stock to the corresponding decile, and creating both equal and value weighted portfolios for each decile. In contrast to this methodology, a novel approach is provided by Stambaugh and Yuan (2017). Using the time-series correlation of long-short portfolios as measure of distance, these authors first separate 11 well-known anomalies found by the asset pricing literature in two clusters. Next, by sorting the stocks according to each "anomalous variable" within each cluster and then computing the average ranking for each stock, Stambaugh and Yuan (2017) create two new factors, called misprising factors, which, in addition to *market* and *size*, can explain the cross-section of stock returns better than four- and five-factors models.

Another contribution to the literature on asset pricing factors model is Frazzini and Pedersen (2014). They investigate the asset pricing implications of a dynamic model with leverage and margin constraints. Their model predicts that, since many investors are constrained in the leverage, they tend to buy high-beta assets to generate high returns. As a result, high beta assets are overpriced whereas low beta assets are underpriced. The authors find evidence in favour of this prediction not only in the US stock market, but also in other asset classes and markets over the world. Moreover, they also show that a betting-against-beta (BAB) factor, that is a portfolio obtained by going long in low-beta assets (leveraged to a beta of 1) and short in high-beta assets (de-leveraged to a beta of 1), generates significant positive risk-adjusted returns.

[6] The investment factor is computed as the average returns difference between firms with high percentage change in total asset and firms with low percentage change in total asset.
[7] The profitability factor is computed as the average returns difference between firms with high ROE and firms with low ROE.

Finally, Adrian, Etula and Muir (2014) provide an intertemporal capital asset pricing model with funding liquidity constraints. Their empirical analysis shows that funding liquidity risk constitutes an important risk factor in the cross-section of stock returns.

3. Macroeconomic-based factors models

Beside the explanatory power of firms' variables, another strand of literature, instead, has focused on the relation between macroeconomic variables and financial markets. For example, Chen, Roll, and Ross (1986) show that industrial production, changes in risk-premium (measured as the difference between portfolios returns of Baa bonds and long-term government bonds), changes in yield curve, and in a weaker way changes in expected inflation and measure of unanticipated inflation can explain the cross-section of asset returns.

Moreover, the growth rate of industrial production can be used to explain variation in momentum portfolio returns (Liu, Warner, and Zhang, 2008), whereas the exposure to the macro-factors proposed by Chen, Roll, and Ross (1986) explains the average return differences between low and high investment firms, and low and high asset growth firms (Cooper and Priestley, 2011). Similarly, Vassalou (2003) shows that news related to future GDP growth rate explain the cross-section of asset returns for book-to-market and size portfolios.

Finally, Cooper, Mitrache, and Priestley (2022) show that portfolios sorted on profitability, investment, BAB, quality, size, momentum and book-to-market ratio can be described by a global-factor model based on Chen, Roll, and Ross (1986) risk factors.

4. Global vs. Country specific asset pricing models

The previous sections highlighted the existence of multiple firms' characteristics related to stock returns, giving also rise to various systematic factors able to explain the cross-section of average returns. Most of this evidence, however, refers only to U.S. firms.

Using a large sample of firms belonging to the U.S. and 12 major EAFE (Europe, Australia, and Far East) countries, instead, Fama and French (1998) confirm the evidence that stocks with high book-to-market, earnings-to-price and cash-flow-to-price earn on average high returns. Furthermore, a model that includes a global (i.e., constructed by using the international sample of firms) *HML* factor in addition to a global market factor captures quite well the average returns of (global) portfolios sorted on *B/M*, *E/P* and *CF/P*.

Following these results, other studies investigated whether the average stock returns of a given country are better explained by a country-specific or a global-based asset pricing model (Griffin, 2002; Fama and French, 2012; Fama and French, 2017; Hollstein, 2022). The corresponding evidence shows that country-specific factors models exhibit a better ability in explaining average stock returns than their global counterparties. As a result, several authors conclude that assets are better priced locally rather than globally.

5. Factors reliability

Over the years, the asset pricing factors related to stock returns have become so numerous and exotic that Cochrane (2011) referred to this proliferation as a "zoo of factors". Obviously, this collection also raises serious concerns regarding the factors reliability, especially due to data mining bias, that is the risk of finding significant relations only by chance.

In this regard, a notable contribution is provided by Novy-Marx (2014). He shows that variables unrelated to economics such as the weather conditions in Manhattan, global warming, sunspot activity, and conjunctions of planets are significantly related to several firms' characteristics which (have been found to) explain the cross-section of stock returns, including momentum, size, book-to-market ratio, and earnings-to-price ratio.

Moreover, Harvey, Liu, and Zhu (2016) claim that the usual *t-stat* criteria used to establish whether a variable is significant in explaining stock returns are not appropriate given the large number of factors, but rather the cutoffs values should be increased to take into account the impact of data mining.

Another critique is addressed by Linnainmaa and Roberts (2016). According to these authors, in fact, if the above factors are not the result of data mining, they should be related to average stock returns also out-of-sample, that is in samples different from the ones used to find them. In this regard, they find that, among 36 firms' characteristics analyzed, less than 50% are statistically significant out-of-sample, thus supporting the concern of data mining for the U.S. dataset.

Hou, Xue, and Zhang (2020), instead, show that, after controlling for the impact of micro-caps stocks (as suggested by Fama and French, 2008), 64% of all the firms' variables analyzed are not significant at the conventional 5% level. Moreover, by raising the *t*-stat cutoff to 3, the number of non-significant variables further increases to 85%. The authors conclude that this evidence might be the result of p-hacking, that is the abuse of data analysis to find statistically significant relations.

6. Evidence on predictability

Over the years, the asset pricing literature has documented the existence of a considerable number of systematic factors based on firms' characteristics that are able to explain the cross-section of stock returns. At the same time, several scholars have investigated the time-series properties of stock returns, focusing in particular on the role played by firms' characteristics in predicting the behavior of future stock returns at different time-horizons.

In this regard, Keim and Stambaugh (1986) show that the logarithm of small firms' share price predicts one-month future excess returns of both small firms and low-grade bonds, exhibiting the strongest ability in January. Regarding the predictive power of other firms' characteristics,

instead, Fama and French (1988, 1989) show that the ability of the dividend yield in explaining future returns, measured by the regression R^2, increases with the horizon of future returns. In addition, this variable seems also to be linked to the business cycle condition since it is high correlated with default spread: it forecasts high returns during weak economic conditions and low returns during strong economic conditions.

Using the aggregated dividend-price ratio and the aggregated book-to-market ratio of all securities included in the Dow Jones Industrial Average (DJIA) index, Kothari and Shenken (1997) show that the former better predicts value-weighted CRSP portfolio returns whereas the latter exhibits a stronger ability in predicting equally-weighted returns.

Similar results have been found by Pontiff and Schall (1998). Specifically, they show that the predictability of the aggregate DJIA book-to-market ratio holds also when controlling for other variables, and in the case of the spread between small and large firms returns during the period 1926-1994. However, their sub-period analysis highlights that the DJIA B/M predictability disappears after 1960, being replaced by the S&P B/M predictability. The authors explain this change by arguing that the composition and the number of securities of S&P is more representative of the U.S. market.

Beside the dividend-price and the book-to-market ratios, Lewellen (2004) shows that the earnings-to-price ratio also contains useful information to predict future returns on both equal- and value-weighted NYSE returns over the period 1963-1994.

A critique of the long-horizon predictability of the dividend-price ratio is provided by Ang and Bekaert (2006). The authors argue that, once correcting for heteroskedasticity and the moving average in error terms generated by summing returns over time, the predictive ability of the dividend-to-price ratio disappears.

Another important contribution is offered by Goyal and Welch (2008) who reexamine the empirical evidence on predictability and show that most models have poor in-sample and out-of-sample performances, thus concluding that equity prediction models are not robust over time.

Focusing on the linkage between macroeconomic and financial markets, Lettau and Ludvigson (2001) document that, over short and mid-term horizons the consumption-wealth ratio (*cay*) has a better ability than the dividend-price ratio in predicting excess stock returns, whereas, at long-term horizons, the dividend yield has a larger power. In addition, Henkel, Martin, and Nardari (2011) confirm that the risk premium is countercyclical, showing higher values during periods of recessions and high volatility. In particular, predictors such as the dividend yield and the term structure are only useful during poor economic conditions.

Finally, focusing on 14 European countries, Jordan, Vivian, and Wohar (2014) show that the out-of-sample forecast performance is linked to country characteristics. Specifically, they find that: 1) fundamentals-price variables (e.g., the dividend yield) are more useful in predicting more liquid markets, 2) macroeconomic variables (e.g, short term rates) are more useful in the

case of developed countries, and 3) the predictive ability of technical variables (e.g., stock volumes and the ratio of rising over falling stocks) is not related to market characteristics.

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