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Risk Factors and Stock Price Performance of U.S. Sectors: A Quintile Approach

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Abstract

The present paper examines the ability of factor pricing models to explain the returns of U.S. stock market sectors. Using monthly data for ten U.S. sectors, from October 1989 to December 2020, classified according to the Global Industry Classification Standards (GICS), we find that asset pricing characteristics vary by industry, however, there are distinct patterns in terms of risk factor loadings and their respective significance depending on whether industries are classified as cyclical or defensive. This suggests that within industries' classification sectors might be, at least at some level, homogenous. Our analysis also reveals that four sectors exhibit an off-pattern behavior, namely Finance, Information Technology, Consumer Staples and Energy. The time period consists of our analysis is quite diverse and includes periods of booming markets, but also extreme recession periods. Thus, we employ quantile regressions to investigate the validity of the models under extreme conditions. Our basic conclusions do not seem to be affected by fat-tails and conditional on the quantile the best performing model may vary, in some sectors.

Keywords

Asset Pricing, Industry Indices, Cyclical vs Non-Cyclical, U.S. Stock Market, Factor Model, Quantile Regression

JEL Classification: C52, G11, G12, G15, M41

1. Introduction and Literature Review

Stock returns are generally challenging to explain, as they consist of many distinct risk channels. The financial literature has been on a never-ending search for a model that explains the cross-section of expected return on assets. In this ongoing research, the U.S. stock market is a global reference market.

Recent studies on the asset pricing field focus either on the ongoing search for factors that explain the cross-section of expected stock returns (Cochrane, 2011; Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016; Hou, Xue, and Zhang, 2017; Feng, Giglio and Xiu, 2020 among others) or on identifying the best model(s) (Hou, Xue, and Zhang, 2020; Stambaugh and Yuan, 2017; Shamim et al., 2018 among others) by incorporating prominent return anomalies as their test assets. The first stream of papers has led to over 450 factors that Cochrane (2011) profiles as a "zoo of factors".

Fama and French (1997) argued that sector-level peculiarities with regard to stock market risk factors are of major importance in capturing variation in stock returns. By generalizing the Fama-French approach to sector-subsets of equities, Papenkov (2019) established a heterogenous industry model that directly accounts for this variation. The findings showed that risk varies significantly across sectors for each of the FF5 components, with distinct subgroups of statistically significant factors within each sector. However, to the best of our knowledge, there is limited attention to sector performance (Dou et al., 2014). Existing literature focuses either on mutual funds (Dellva, DeMaskey and Smith, 2001; Faff, 2004; Kacperczyk, Sialm and Zheng, 2005) or sector rotation strategies (Sorensen and Burke, 1986; Grauer, Hakansson and Shen, 1990; Sassetti and Tani, 2006; Conover et al., 2008; Baca, Garbe and Weiss, 2000; Conover et al., 2005; Shynkevich, 2013; Dou et al., 2014).

Jensen et al. (2021) highlight the significance of replicating studies in validating proposed risk factors, either by using the same sample and time period or under different samples and time periods. Our present paper builds on this notion. We take a step back and examine the predictive ability of well documented risk factors in explaining as simple formations as sector indices stock returns. Although our test asset might seem to be simple it is of great economic and investment importance. Notably, we examine the ability of ten different factor pricing models to explain the average excess returns of monthly indices for ten U.S. stock market sectors, namely the Consumer Discretionary, Financials, Industrials, Information Technology, Materials, Consumer Staples, Energy, Healthcare, Telecommunication Services and Utilities.

Following Shamim et al. (2018), we also incorporate the capital asset pricing model of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, the Fama and French (1993) and Pastor and Stambaugh (2003, 2019) four-factor model, the Asness and Frazzini (2013) three-factor model, the Hou, Xue, and Zhang (2015) q-factor model, the Fama and French (2015) five-factor model, the Fama and French (2015) four-factor model that reduces the value factor, the Stambaugh and Yuan (2017) four-factor model, and the Barillas and Shanken (2018) six-factor model.

Our baseline results indicate that asset pricing characteristics vary by industry

(Papenkov, 2019). However, there are distinct patterns in terms of risk factor coefficients and statistical significance within each categorization, depending on whether industries are classified as cyclical or defensive. This finding suggests that within industries' classification, sectors might be, at least to some extent, homogenous. Our analysis also reveals that four sectors exhibit an off-pattern behavior. These industries are Finance, Information Technology, Consumer Staples and Energy. Therefore, from an investment perspective, it is important to pay special attention to the characteristics of these sectors' risk-return.

Barillas and Shanken (2018) argue that many of the factors are just different versions of the same underlying construct. Our analysis contributes to this line of research by revealing the interactions and patterns of several risk factors. Remarkably, the HML Devil factor is slightly weaker as a prognostic factor than the FF HML factor. However, the FF HML factor seems to strongly interact with RMW and CMA (Fama & French, 2015). The size, investment and profitability factors of the FF are stronger than those constructed by the HXZ in both coefficient loadings and statistical significance. Furthermore, HXZ's investment factor is strongly affected by HML Devil, since its explanatory power has been mitigated. The momentum risk factor exhibits its weakest performance when the HML Devil, the investment and profitability risk factors are incorporated. This finding is in line with Hou, Xue, and Zhang (2015) and contradicts the findings of Barillas and Shanken (2018). Overall, we simply highlight that common risk factors designed to capture the same effect under different construction options, exhibit variations in their coefficient loadings and are statistically significant in different sectors.

However, one should consider that stock return series are notorious for containing extreme values due to erratic market reaction to news. To that end, we also apply the quantile regression approach in order to investigate whether our findings are robust under the presence of outliers and fat-tails. Following the argumentation provided by González and Jareño (2019), we also interpret quantiles as follows: higher values of θ are associated with periods of expansion, and lower values are associated with periods of recession. Quantile regressions provide qualitatively similar results to those of OLS regressions in respect to rate indices and statistical significance of asset pricing factors.

The rest of the paper is organized as follows. Section 2 describes the data and models used in this study. Section 3 presents and comments on the main results of our assessments, and finally, Section 4 offers concluding remarks.

2. Data Description

Our data includes monthly returns of the indices for the ten U.S. stock market sectors from October 1989 to December 2020. Market sectors are classified into cyclical and non-cyclical in line with the MSCI. Consumer Discretionary, Finance, Industrials, Information Technology and Materials as cyclical sectors. Consumer Staples, Energy, Healthcare, Telecommunication Services and Utilities are classified as Defensive sectors.

Data for the explanatory variables come from multiple sources. Time series data on the risk factors associated with the CAPM and FF models (MKT, SMB, HML, RMW, and CMA) come from the Kenneth French's data library. Additional published factors are then retrieved directly from the authors' websites, namely liquidity (LIQ) by Pastor and Stambaugh (2003, 2019), the q-factors (R_MKT, R_ME, R_IA, R_ROE and R_EG) by Hou, Xue, and Zhang (2015) and the four factors (MKTRF, MGMT, and PERF) by Stambaugh and Yuan (2017). Finally, we also include the HML Devil factor by Asness and Frazzini (2013) from the AQR data library.

We examine the ability of ten different factor pricing models to explain the average excess returns of monthly indices for the ten U.S. stock market sectors mentioned above. These models are:

The capital asset pricing model (CAPM), Model 1

$$R_{i,t} = \alpha + \beta MRF_t + \varepsilon_{i,t} \tag{1}$$

The Fama & French (1993) three-factor model (FF3), Model 2

$$R_{i,t} = \alpha + \beta MRF_t + sSMB_t + hHML_t + \varepsilon_{i,t} \tag{2}$$

The Asness and Frazzini (2013) three-factor model (FFAF), Model 3

$$R_{i,t} = \alpha + \beta MRF_t + sSMB_t + hHMLDevil_t + \varepsilon_{i,t} \tag{3}$$

The Fama and French (1993) and Carhart (1997) four-factor model (FFC), Model 4

$$R_{i,t} = \alpha + \beta MRF_t + sSMB_t + hHML_t + MOM_t + \varepsilon_{i,t} \tag{4}$$

The Fama and French (1993) and Pastor and Stambaugh (2003, 2019) four-factor model (FFPS), Model 5

$$R_{i,t} = \alpha + \beta MRF_t + sSMB_t + hHML_t + lLIQ_t + \varepsilon_{i,t} \tag{5}$$

The Fama & French (2015) five-factor model (FF5), Model 6

$$R_{i,t} = \alpha + \beta MRF_t + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_{i,t} \tag{6}$$

The Fama & French (2015) four-factor model (FF4), Model 7

$$R_{i,t} = \alpha + \beta MRF_t + sSMB_t + rRMW_t + cCMA_t + \varepsilon_{i,t} \tag{7}$$

The Hou, Xue, and Zhang (2015) q-factor model (HXZ), Model 8

$$R_{i,t} = \alpha + \beta R\_MKT_t + mR\_ME_t + iR\_IA_t + rR\_ROE_t + \varepsilon_{i,t} \tag{8}$$

The Barillas and Shanken (2018) six-factor model (BS6), Model 9

$$R_{i,t} = \alpha + \beta MRF_t + sSMB_t + hHML_t + MOM_t + iR\_IA_t + rR\_ROE_t + \varepsilon_{i,t} \tag{9}$$

The Stambaugh and Yuan (2017) four-factor model (SY4), Model 10

$$R_{i,t} = \alpha + \beta MKTRF_t + sSMB_t + mMGMT_t + pPERF_t + \varepsilon_{i,t} \tag{10}$$

where $R_{i,t}$ is the period t monthly return on sector index i in excess of the risk-free rate; MRF_t, SMB_t and HML_t are, respectively, the market, size, and value factors of Fama and French (1993); LIQ_t is the trading liquidity factor of

Pastor and Stambaugh (2003, 2019); $HMLDevil_t$ is the value factor of Asness and Frazzini (2013); RMW_t, CMA_t and MOM_t are, respectively, the profitability, investment, and momentum factors of Fama and French (2015, 2016); R_MKT_t, R_ME_t, R_IA_t and R_ROE_t are, respectively, the size, investment, and profitability factors of Hou, Xue, and Zhang (2015); and SMB_t, $MGMT_t$ and $PERF_t$ are the size and two mispricing factors of Stambaugh and Yuan (2017), respectively.

3. Results

3.1. Baseline Results: OLS Regressions

In this subsection, we estimate time series regressions, using standard OLS regression, of the ten different factor models. Fama and French (2015) and Racicot and Théoret (2016), among others, argue that a model that completely captures expected returns should have an intercept close to zero. Thus, if the inclusion of new factors leads to a significant reduction of the intercept, this will also indicate that a significant constant term in an asset pricing model may be due to specification errors, such as the omission of relevant variables. All models seem to adequately record expected returns, since the constant term is mainly statistically indistinguishable from zero, or in cases where the intercept is statistically significant, its coefficient loading is quite low. **Tables 1-3** report coefficients estimates from these time series regressions.

3.2. Industry-Oriented Discussion

We begin our analysis by investigating whether cyclical and defensive sectors' stock returns exhibit variations in common risk factors. Defensive sectors are considered to repeatedly outperform the market when economic growth slows down, since they produce or sell goods/services that we keep on using even when money is tight. On the other hand, cyclical sectors are considered to be directly related to the economy, since they sell goods or services that consumers buy when the economy is doing well but shrink during downturns.

Notably, **Table 1** reports coefficients estimates from time series regressions of five different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), Model 1; the Fama and French (1993) three-factor (FF3) model, Model 2; the Asness and Frazzini (2013) three-factor (FFAF) model, Model 3; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, Model 4 and the Fama and French (1993) and Pastor and Stambaugh (2003, 2019) four-factor (FFPS) model, Model 5.

Tabulated results verify that cyclical industries are closely related to market downtrends and expansions, since their beta coefficients are above 1. However, it could be argued that non-cyclical industries can be further classified based on their sticky demand. Sticky demand industries with, such as Utilities, have lower market beta coefficients than non-cyclical industries with less sticky demand. Notably, energy sector has market betas close to 1, although it is classified as a defensive sector by the MSCI. This finding might be attributed to the fact that Energy sector includes Oil companies. Oil prices are more sensitive to market's downtrends and expansions, resulting in higher market beta estimates.

Table 1. The table reports coefficients estimates from time series regressions of five different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), Model 1; the Fama and French (1993) three-factor (FF3) model, Model 2; the Asness and Frazzini (2013) three-factor (FFAF) model, Model 3; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, Model 4 and the Fama and French (1993) and Pastor and Stambaugh (2003, 2019) four-factor (FFPS) model, Model 5. The above-mentioned monthly time series regressions are estimated for ten different industries, using their monthly stock returns as our depended variable. The t-statistics adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level respectively.

Time series Regressions: Five Different Models-Ten Different Industries (Returns)										
	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 1: CAPM										
MKT	1.0527***	1.1686***	1.0354***	1.3058***	1.0292***	0.5292***	0.8804***	0.6587***	0.7693***	0.3737***
Model 2: FF3										
MKT	1.0701***	1.2730***	1.0758***	1.2617***	1.0649***	0.6015***	0.9209***	0.7282***	0.8422***	0.4364***
SMB	−0.0418	−0.2584***	−0.0950*	−0.0364	−0.0372	−0.3447***	0.0035	−0.4031***	−0.4336***	−0.2504***
HML	0.1306***	0.7687***	0.3082***	−0.6547***	0.3786***	0.1571**	0.5341***	−0.0128	−0.0367	0.2460***
Model 3: FFAF										
MKT	1.0425***	1.1632***	1.0292***	1.3461***	1.0035***	0.5862***	0.8360***	0.7350***	0.8373***	0.4039***
SMB	−0.0453	−0.2844***	−0.1015**	−0.0177	−0.0483	−0.3479***	−0.0155	−0.4036***	−0.4365***	−0.2568***
HML Devil	0.1766***	0.4914***	0.2338***	−0.3358***	0.3216***	0.0341	0.4268***	−0.0613	0.0680	0.1356**
Model 4: FFC										
MKT	1.0294***	1.2400***	1.0522***	1.2112***	1.0323***	0.6266***	0.9222***	0.7455***	0.8331***	0.4778***
SMB	−0.0393	−0.2564***	−0.0936**	−0.0333	−0.0352	−0.3462***	0.0034	−0.4042***	−0.4330***	−0.2529***
HML	0.0838*	0.7307***	0.2811***	−0.7128***	0.3411***	0.1860**	0.5356***	0.0072	−0.0472	0.2937***
MOM	−0.1200***	−0.0975***	−0.0696***	−0.1491***	−0.0962	0.0741*	0.0038	0.0511	−0.0270	0.1223***
Model 5: FFPS										
MKT	1.0722***	1.3102***	1.0848***	1.2739***	1.0704***	0.5976***	0.8042***	0.7321***	0.8151***	0.4326***
SMB	−0.0194	−0.2563***	−0.0976*	−0.0375	−0.0347	−0.3390***	−0.0826	−0.4094***	−0.4583***	−0.2474***
HML	0.1555***	0.7890***	0.3053***	−0.6674***	0.4279***	0.1541*	0.4222***	−0.0318	−0.0704	0.2404***
LIQ	−0.0305	−0.0900*	−0.0097	0.0252	0.2611***	−0.0158	0.3609***	−0.1128***	0.0213	0.1002

Table 2. The table reports coefficients estimates from time series regressions of three different factor models: the Fama and French (2015) five-factor (FF5) model, Model 6; the four-factor (FF4) model that excludes the value factor from the FF5 model, Model 7; and the Hou, Xue, and Zhang (2015) q-factor (HXZ) model, Model 8. The above-mentioned monthly time series regressions are estimated for ten different industries, using their monthly stock returns as our depended variable. The t-statistics adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level respectively.

Time series Regressions: Three Different Models-Ten Different Industries (Returns)										
	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 6: FF5										
MKT	1.0926***	1.2093***	1.1201***	1.1358***	1.1469***	0.7664***	0.9909***	0.8353***	0.9253***	0.5047***
SMB	0.0445	−0.2800***	−0.0222	−0.1538*	0.0600	−0.1600***	0.0772	−0.3020***	−0.4305***	−0.2512***
HML	0.1001	0.9405***	0.2110***	−0.3440***	0.1843**	−0.2380***	0.3648**	−0.2767***	−0.2705**	0.0526
RMW	0.2665***	−0.1020	0.2403***	−0.4205***	0.3346***	0.6413***	0.2583*	0.3612***	0.0594	0.0391
CMA	−0.0983	−0.3595***	0.0842	−0.4960***	0.2635**	0.5611***	0.2513	0.4186***	0.5410**	0.4541***
Model 7: FF4										
MKT	1.1073***	1.3471***	1.1510***	1.0854***	1.1739***	0.7315***	1.0443***	0.7947***	0.8857***	0.5124***
SMB	0.0529	−0.2009***	−0.0044	−0.1828**	0.0755	−0.1800***	0.1079	−0.3253***	−0.4533***	−0.2467***
RMW	0.3045***	0.2558**	0.3205***	−0.5513***	0.4047***	0.5508***	0.3970***	0.2560***	−0.0435	0.0592
CMA	−0.0022	0.5435***	0.2868***	−0.8262***	0.4404***	0.3326***	0.6015***	0.1530	0.2813	0.5046***
Model 8: HXZ										
MRP	1.0511***	1.2738***	1.1022***	1.2354***	1.0804***	0.6888***	0.7931***	0.8014***	0.8029***	0.4394***
ME	0.0001	0.0010	0.0003	−0.0030***	0.0016**	−0.0003	0.0021**	−0.0016	−0.0034***	0.0002
IA	−0.0002	0.0046***	0.0026***	−0.0056***	0.0044***	0.0018*	0.0030**	0.0002	0.0002	0.0029*
ROE	0.0002	0.0027**	0.0018**	−0.0042***	0.0012	0.0055***	0.0013	0.0043***	−0.0004	0.0016

Table 3. The table reports coefficients estimates from time series regressions of two different factor models: the Barillas and Shanken (2018) six-factor (BS6) model, Model 9; and the Stambaugh and Yuan (2017) four-factor (SY4) model, Model 10. The above-mentioned monthly time series regressions are estimated for ten different industries, using their monthly stock returns as our depended variable. The t-statistics adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level respectively.

Time series Regressions: Two Different Models-Ten Different Industries (Returns)										
	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 9: BS6										
MKT	1.0429***	1.2967***	1.1012***	1.1787***	1.0964***	0.6909***	0.8435***	0.7904***	0.7936***	0.4805***
SMB	0.0347	−0.1721***	−0.0166	−0.1290	0.0350	−0.1880***	−0.0703	−0.3085***	−0.5334***	−0.2772***

Continued

IA	−0.0010	0.0009	0.0013*	−0.0007	0.0024	0.0015	−0.0008	0.0011	−0.0003	−0.0003
ROE	0.0017**	0.0039***	0.0030***	−0.0045***	0.0027**	0.0054***	0.0009	0.0035***	−0.0026*	−0.0003
HML Devil	0.1731***	0.6274***	0.2410***	−0.7032***	0.3381***	0.0733	0.5508***	−0.1133	0.0932	0.4448***
MOM	−0.0844*	0.0544	−0.0483	−0.3378***	−0.0290	−0.0418	0.2639***	−0.0904	0.1041	0.3301***
Model 10: SY4										
MKT	1.0491***	1.2387***	1.1048***	1.2102***	1.1260***	0.7826***	0.7949***	0.8308***	0.8920***	0.5374***
SMBm	−0.0176	−0.1960**	−0.1001	−0.0914	−0.0230	−0.2713***	−0.1312	−0.3930***	−0.5913***	−0.2307***
MGMT	0.1270***	0.6342***	0.2809***	−0.6174***	0.3192***	0.3819***	0.1013	0.1816**	0.0727	0.2531**
PERF	−0.0862**	−0.3638***	−0.0430	0.0624	−0.0320	0.2275***	0.0279	0.1524*	0.0948	0.0921

Defensive sectors' returns are negatively related to the size risk factors and mainly unrelated to the momentum and liquidity risk factors (Papenkov, 2019). The negative sign of SMB suggests that non-cyclical sectors are mainly characterized by large sized firms. Indeed, top constituents of non-cyclical industries are among the top 100 largest listed companies in the U.S., and thus it is only natural to expect SMB to be negatively related to these industries' stock returns. MOM is statistically indistinguishable from zero for stocks of defensive sectors. Given that non-cyclical sectors repeatedly outperform the market there is no sense in a risk premium built upon past performance.

LIQ risk factor is statistically significant only in two defensive sectors, namely Energy and Health Care. It is positively related to Energy's stock returns but negatively related to the stock returns of Health Care. The positive sign of LIQ in Energy is in line with the findings provided by Sklavos et al. (2013), who showed a positive interrelationship between depth, volume turnover and breadth, and suggested liquidity persistence due to the presence of informed trading. The negative sign on LIQ for the Health Care sector suggests that its stocks are less sensitive to liquidity shocks, due to high anelastic demand for their provided services.

Finally, although it seems that defensive sectors' stock returns are positively related to value risk factors, special attention must be paid to the fact that a) HML turns negative under the presence of an investment risk factor and b) Asness and Frazzini's (2013) HML Devil risk factor is proved to be a statistically significant determinant mainly for stock returns of cyclical industries. A positive sign on the value risk factors suggests that defensive sectors are characterized by distressed firms. This finding might be consistent with the fact that a traditionally non-cyclical sector, i.e., the non-cyclical consumer sector, has undergone a rapid credit change. Specifically, in 2018 a Credit Suisse study revealed that the non-cyclical consumer sector had the highest notional amount of credit rating downgrades from A- to BBB.

On the other hand, a negative sign on the value risk factors or a statistically insignificant value risk factor suggests that defensive sectors are either characterized by strong fundamentals or their fundamentals do not affect their stock returns. Both these findings are consistent with their profile as firms with strong cash flows and stable operations with the ability to withstand weakening economic conditions. They also pay dividends, which can have the effect of cushioning a stock's price during a market decline. That being said and by taking into account that value risk factors are perceived to highly interact with profitability and investment risk factors (Fama and French, 2015) or that the value factor HML contains similar information to an investment growth factor (Xing, 2008; Hou, Xue, and Zhang, 2015), we can only assume that the latter scenario of a negative or statistically insignificant value risk factor applies to the stock returns of defensive sectors.

Stock returns of cyclical sectors are positively related to the value risk factors and negatively related to the momentum risk factor. The size and liquidity risk factors are not proved to be strong determinants of their stock returns. Since cyclical sectors are led by market's upturns and downturns, SMB and LIQ are not expected to explain their stock returns, in the sense that both small (sensitive to liquidity shocks) and large (least sensitive to liquidity shocks) firms in cyclical sectors are generally affected by the overall economy. Thus, we argue that there is no point in a risk premium for these factors. The positive and statistically significant loading of HML is consistent with documented findings from industry specific-studies (e.g. Elyasiani et al., 2011; Mohanty et al., 2021). The negative sign of MOM suggests that cyclical sectors are dominated by past losers. We attribute this feature to our under-examination time period, in particular 1989-2020. Within this period, we have at least two major financial crises, the Great Recession from December 2007 to June 2009, as well as the ongoing global economic recession in the immediate aftermath of the COVID-19 pandemic.

Table 2 reports coefficients estimates from time series regressions from time series regressions of factor models that include an investment and a profitability risk factor; namely, the Fama and French (2015) five-factor (FF5) model, Model 6; the four-factor (FF4) model that excludes the value factor from the FF5 model, Model 7; and the Hou, Xue, and Zhang (2015) q-factor (HXZ) model, Model 8.

The profitability risk factor carries positive and statistically significant coefficients in both industry classifications under the FF construction options. Top constituents of both industry classifications are dominated by profitable firms. The investment risk factor presents some interesting results. First, it is proved to be a strong determinant of stock returns in both classifications. Then, under the presence of a statistically significant and positive HML, the CMA risk factor in cyclical industries is mainly negatively related to stock returns or statistically indistinguishable from zero.

On the other hand, under the omission of HML, investment risk factors (CMA and IA) are positively related to subsequent stock returns in cyclical industries. In the latter case, the only exception is Information Technology. This finding is inconsistent with a redundant HML factor, but in line with the general perception that it interacts at least with CMA risk factor (Fama and French, 2015). Overall, a positive investment risk factor in both industry classifications, indicating the dominance of conservative investment, might be attributed to the fact that under at least two great recessions, firms of both classifications are reluctant towards aggressive investments due to the greater uncertainty about future economic circumstances. Finally, it should be noted that, under HXZ's construction options both factors perform poorly.

Finally, we examine asset pricing models that cannot be directly compared, either because they incorporate a mixture of the above-mentioned risk factors or because they incorporate "clustered" risk factors representing multiple anomalies, with the same bottom line, in one variable. Notably, **Table 3** reports coefficients estimates from time series regressions of two different factor models: the Barillas and Shanken (2018) six-factor (BS6) model, Model 9; and the Stambaugh and Yuan (2017) four-factor (SY4) model, Model 10.

When, we employ the BS6 model our initial conclusions remain more or less the same. SMB remains negative and statistically significant only in defensive sectors, whereas HML Devil remains positive and statistically significant only in cyclical industries. IA exhibits the same weak behavior as previously reported. On the other hand, the initial weak performance of ROE turns into a strong positive determinant of future stock returns in cyclical industries. The stronger HML Devil and ROE performance is in line with the finding that the value risk factor interacts with both profitability and investment risk factors (Fama and French, 2015). Stambaugh and Yuan (2017) propose two mispricing factors: MGMT and PERF. The MGMT factor results from clustering six anomalies (namely, net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment-to-assets) that can be directly affected by business management. The PERF factor results from clustering five anomalies (namely, financial distress, O-score, momentum, gross profitability, and return-on-assets) that are related to performance and less likely to be affected by managers. Both factors are the average of undervalued portfolio returns minus the average of overvalued portfolio returns. The MGMT mispricing factor seems to be an important determinant of stock returns mainly in cyclical industries. It is positively related to stock returns of industries except the Information Technology sector. The PERF mispricing factor does not exhibit the same powerful presence since it is mainly statistically insignificant.

The fact that a mispricing factor is proved to be statistically significant in cyclical industries can be attributed to the low response to the seasonal earnings of cyclical industries. Although investors adjust their expectations upward for seasonality, they do not adjust enough, consistently declining to positive seasonal-earnings announcements. This may be attributed to a behavioral constraint that requires attention. Investors are considered to focus more on recent data. That is, that low-performing recent quarters shape investors' expectations, while a higher performance from the same quarter in the previous year is ignored.

This explanation is in line with the availability heuristic from behavioral finance, an intellectual shortcut that investors follow relying on the most recent examples.

The analysis up to this point draws our attention to four specific industries that exhibit an off-pattern behavior. First, Information Technology (a cyclical sector with market beta above 1) is characterized by negative value factors, investment factors and profitability factors. It has the strongest momentum effect and a negative MGMT risk factor. In general, the Information Technology sector is characterized by rapid depreciation products and/or services and fast-growing firms. Thus, taking into account that the value, the profitability, the investment risk and the MGMT factors carry a negative slope, we argue that their stock returns follow the patterns of fast-growing non-profit overvalued companies (Fama and French, 2015). Following the idea that investments in Information Technology are inherently risky due to industry uncertainty about the economic impact, technological complexity, rapid obsolescence, implementation challenges etc., we can only expect that MOM should exhibit its highest negative value.

Furthermore, Financials exhibit the highest values in HML (HML Devil), market and MGMT factors, and statistically significant negative size, MOM and PERF factors. Barber and Lyon (1997) show that value and size risk factors tend to explain stock returns of financial firms listed on the NYSE from 1973 to 1994 in a similar way to non-financial ones. Stiroh and Schuermann (2006) compare several pricing models in a sample of banking stocks observed from 1997 to 2005 and conclude that market, value, and size risk factors are the most important in explaining changes in stock returns. Viale et al. (2009) test the CAPM, the FF3 model, and the ICAPM on a sample of US financial firms over the period 1986-2003 and conclude that 1) the ICAPM is the most effective, 2) the FF3 model does not perform significantly better than the CAPM, and 3) the value premium is a better predictor than size premium. Baek and Bilson (2005), in a sample of financial and non-financial US firms analyzed from 1963 to 2012, argue that the FF3 model works worse if applied to financial firms, but can be used to price bank stocks adequately. The financials industry index mainly comprises of diversified financials and banks. The negative size factor is in line with the findings of Viale, Kolari and Fraser (2009), who concluded that the returns of large banks are higher than their smaller counterparts. The higher market betas of industries, in the sense that the industry is dominated by large cap firms, is in line with the results provided by Elyasiani, Mansur and Pagano (2007), who examined market betas for US banks and reported that the systematic risk exposure of large banks is significantly higher than that of small banks. The finding that large banks take on greater market risk than their smaller counterparts is consistent with Demsetz and Strahan (1995, 1997).

The recent global financial crisis that originated in the US demonstrates that equity markets are vulnerable to changes in banking risk such as credit risk, liquidity risk and insolvency risk. That is, poor risk management of bank along with other market factors can lead to banking failures, which can cause financial turmoil in the whole equity market (Bartram and Bodnar, 2009). The higher market betas of large banks are possibly due to their higher credit risk, higher financial leverage, more extensive engagement in off-balance sheet activities (e.g., trading, and derivative positions), and the more aggressive attitudes of their managers toward risk. The fact that value factors present their highest values suggests that a proxy of financial distress is essential in explaining financial firms' stock return patterns. Furthermore, this finding is further reinforced, given that in the presence of a statistically strong and positive value risk factor the investment risk factors become statistically insignificant or carry a negative sign.

Following the notion that investors still remember recent global financial crisis caused by the poor risk management of large financial firms and banks, we can only expect MOM to show its highest negative value. The fact that both mispricing factors are statistically significant reveals that market participants do not properly value financial firms, probably due to the complex composition of the bank's risk which is clearly influenced by the type of firm investment, diversification opportunities, and financial leverage decisions. This finding is also confirmed by the fact that MGMT is positively related to industry's stock returns (undervalued stocks based on quantities that firms' management can directly affect), while PERF is negatively related to industry's stock returns (overvalued stocks based on firm's performance measures that firms' management cannot directly affect).

In respect to noncyclical sectors, Consumers Staples are characterized by the strongest profitability and PERF factors. The Consumer Staples sector includes food, beverage, and tobacco products; and food distributors (e.g., supermarkets, hypermarkets); non-durable household goods (e.g., detergent and diapers) and personal products (e.g., shampoo and cosmetics). Its goods and services are always in demand, regardless of the overall market circumstances. During the COVID19 pandemic, retailers within the sector have aggressively cut costs, leaving them in reasonable financial condition. This explains why the profitability risk factor has its highest value in Consumer Staples industry. Furthermore, an improving economy and strong stock market historically made this defensive sector relatively less attractive to investors. If we also take into account that the sector typically has a stable earnings profile, PERF should be a strong determinant and positively related to its stock returns.

The energy sector must be given special consideration. First, although it is classified as a defensive sector by the MSCI, its market beta is close to 1 and in some cases slightly above 1. Its stock returns are still positively related to value risk factors, even when profitability and investment are considered. In fact, when we employ the BS6 model, the only factors driving its stock returns are HML Devil and MOM (besides the market risk factor). LIQ is positively related to the industry's stock returns, whereas size and mispricing risk factors are statistically indistinguishable from zero.

LIQ's positive sign, as we have already mentioned, can be attributed to liquidity maintenance due to the presence of up-to-date transactions. However, it should also be considered that OPEC members seem to be less cohesive, leading to higher volatility in oil prices. We attribute the positive value risk factor of Energy Sector to its newly emerged risks. First, there is the increasingly onerous regulatory environment. Then, media report a recent interruption in talks between OPEC+ members and a subsequent call for lower oil prices by the Biden administration that causes a growing uncertainty. Finally, there is also the trend towards clean energy that could lead to a reduced oil demand in the long term. Finally, MOM's positive relation to industry's stock returns is probably due to the fact that equity analysts have found optimism amid the combination of rising oil prices that boost revenues and restrain expense growth.

3.3. Factor-Oriented Discussion

Barillas and Shanken (2018) argue that several of the factors are simply different versions of the same underlying construction, namely size (SMB or ME), profitability (RMW or ROE), value (HML or HML Devil) and investment (CMA or IA). Investors are frequently subject to model uncertainty and margin constraints, which hinder them from implementing certain extreme investment strategies proposed by asset pricing models, according to Pastor and Stambaugh (2000). In this framework, our analysis revealed some interesting patterns in respect to the employed risk factors' performance.

The HML Devil factor is slightly weaker as a predictor than the FF HML factor, in terms of coefficient loading. Asness and Frazzini (2013) construct their value factor in a more "timely" manner, based on B/M rankings that employ the most recent monthly denomination stock price. Since MKT's explanatory power for subsequent stock returns is mitigated and HML Devil's loadings are not as high as the original HML's factor, we argue that the information collected by the latter is to some extend already incorporated by the former and thus leading both variables' coefficients downwards. However, the FF HML factor seems to strongly interact with RMW and CMA (Fama & French, 2015) in the case of noncyclical sectors, since its coefficient loading changes from positive to negative. On the other hand, the HML Devil risk factor does not exhibit the same behavior (Barillas and Shanken, 2018).

The size, investment and profitability factors of the FF are stronger than the ones made by the HXZ both in coefficient loadings and statistical significance. Skočir and Loncarski (2018) examine existing asset pricing risk factors, although their analysis reveals that the incorporation of different stock allocation and different construction options into different factors has some, but limited, effect. However, Shamim et al. (2018) implicitly suggest that different construction options of existing asset pricing factors may lead to different results. Furthermore, HXZ's investment factor is strongly influenced by HML Devil, since its explanatory power has been mitigated. A feature of HXZ's excess return factors that distinguishes them from those of other asset pricing model factors is that they are made by using stocks of non-financial firms with a nonnegative B/M only. Another key difference is that the profitability factor ROE is derived from monthly sorts on ROE, whereas RMW is from annual sorts on Operating Profitability. However, it should be noted here that both models examine risk factors' explanatory power on factor portfolio returns rather than sector indices returns. Thus, besides their structural differences, their test assets and empirical design have a different purpose than ours. Overall, we simply highlight that common risk factors designed to capture the same effect under different construction options, exhibit variations in their coefficient loadings and statistical significant in different sectors.

Momentum risk factors exhibit their weakest performance when the HML Devil, the investment and profitability risk factors are incorporated. This finding is in line with Hou, Xue, and Zhang (2015) and contradicts the findings of Barillas and Shanken (2018). Since the momentum risk factor is mainly statistically insignificant in both BS6 and the FFC models, we argue that these findings might be consistent with recent evidence on the disappearance of the momentum premium (Mclean and Pontiff, 2016; Hwang and Rubesam, 2015).

Finally, we can easily observe that the MGMT factor (management oriented mispricing factor) prevails over the PERF factor (performance oriented mispricing factor). One possible interpretation is that investors pay closer attention to quantities directly affected by firms' management, in the sense that they might entail information about a firm that only its management is aware of. The mispricing factor related to firms' performance probably needs a technical evaluation and expertise that not all investors have, in order to be judged/valued properly, a fact that leads to its statistical insignificance.

3.4. Robustness Test: Quantile Regressions

When we want to understand the central tendency in a dataset, OLS is an effective method. However, OLS loses its effectiveness when we try to exceed the median value or towards the extremes of a data set. The quantile regression approach allows for many parameters to be taken as explanatory variables included in each model. Thus, β_{ij}^{θ} measures the sensitivity of the return on sector j at the θth quantile in the movements of the factor i. This makes the quantile regression robust to the presence of outliers.

A stock return series is notorious for containing extreme values due to erratic market reaction to news. If we further take into account that our time period consists of sub-periods of blooming markets but also extreme recession periods, it is only natural to ask whether our findings are robust under the presence of outliers and fat-tails. Among others, Barnes and Hughes (2002) applied quantile regression to study the capital asset pricing model (CAPM). Allen and Powell (2011) used quantile regression to study the Fama-French three-factor model. In line with the argumentation provided by González and Jareño (2019), we interpret quantiles as follows: higher values of θ are associated with expansion periods, and lower values are associated with recession periods. **Tables 4-6**

Table 4. The table reports coefficients estimates from time series regressions of five different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), Model 1; the Fama and French (1993) three-factor (FF3) model, Model 2; the Asness and Frazzini (2013) three-factor (FFAF) model, Model 3; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, Model 4 and the Fama and French (1993) and Pastor and Stambaugh (2003, 2019) four-factor (FFPS) model, Model 5. The above-mentioned monthly time series regressions are estimated for ten different industries for quintiles 0.10 (a) and 0.90 (b), using their monthly stock returns as our depended variable. The t-statistics adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level respectively.

(a)

Time series Regressions: Five Different Models-Ten Different Industries Returns (Quintile 0.10)										
Q = *0.10*	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 1: CAPM										
MKT	1.0644***	1.1900***	1.0536***	1.3151***	1.0607***	0.5705***	0.8320***	0.7250***	0.8375***	0.4265***
Model 2: FF3										
MKT	1.0909***	1.3095***	1.0914***	1.2430***	1.1919***	0.6121***	0.8733***	0.7142***	0.8479***	0.5517***
SMB	−0.0450	−0.1920*	−0.1561**	0.1214	−0.0927	−0.3108**	0.0463	−0.3747***	−0.2964**	−0.2149
HML	0.1468**	0.8213***	0.2788***	−0.9106***	0.4338***	0.1278	0.4792***	−0.0926	−0.0288	0.2331
Model 3: FFAF										
MKT	1.0438***	1.1346***	1.0895***	1.4464***	1.0071***	0.6342***	0.8330***	0.7132***	0.8615***	0.5126***
SMB	−0.1302	−0.2426***	−0.1729**	0.0549	−0.1323	−0.2855**	0.0420	−0.3650***	−0.3091**	−0.2753
HML Devil	0.1462**	0.4269***	0.2393***	−0.5371***	0.3388***	0.0533	0.2507	−0.0873	−0.0276	0.0741
Model 4: FFC										
MKT	1.0238***	1.2451***	1.0981***	1.1092***	1.0728***	0.6395***	0.8907***	0.7073***	0.8414***	0.6493***
SMB	−0.1173	−0.1425*	−0.1876***	0.1129	−0.1730	−0.1855	0.0207	−0.3845***	−0.3621***	−0.2242
HML	0.1066*	0.7869***	0.2775***	−0.8499***	0.4172***	0.1962**	0.6085***	−0.0682	−0.0245	0.2872*
MOM	−0.1432***	−0.0792	−0.0266	−0.1694**	−0.1031	0.1314	0.0928	0.0300	0.0680	0.1629
Model 5: FFPS										
MKT	1.1007***	1.3682***	1.1342***	1.2664***	1.0803***	0.6346***	0.8375***	0.6970***	0.8369***	0.6025***
SMB	−0.0309	−0.2411***	−0.1047	0.1506	−0.0337	−0.3118**	−0.0425	−0.3852***	−0.3084**	−0.2300
HML	0.2124***	0.8259***	0.3299***	−0.9625***	0.5632***	0.1521	0.4340***	−0.0977	−0.0504	0.1845
LIQ	−0.0139	−0.1341*	−0.0749	0.0625	0.2349**	−0.0645	0.2096*	−0.0618	−0.0497	0.1390

(b)

Time series Regressions: Five Different Models-Ten Different Industries Returns (Quintile 0.90)										
Q = 0.90	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 1: CAPM										
MKT	1.0885***	1.0270***	0.9831***	1.3455***	1.0905***	0.3733***	0.7819***	0.6386***	0.6137***	0.2078**
Model 2: FF3										
MKT	1.0949***	1.2631***	1.0599***	1.3350***	1.0294***	0.5202***	0.8585***	0.7306***	0.7606***	0.2992***
SMB	−0.0641	0.8585***	−0.0783	−0.165	−0.0187	−0.3673***	−0.2263*	−0.4249***	−0.5154***	−0.1523
HML	0.139	0.7705***	0.3571***	−0.6817***	0.3259**	0.2887***	0.3525***	0.1114	−0.0349	0.3083**
Model 3: FFAF										
MKT	1.0627***	1.1085***	1.0241***	1.3626***	0.9363***	0.4537***	0.8336***	0.7081***	0.7449***	0.3056***
SMB	−0.1318*	−0.2830**	−0.1570**	−0.0466	0.0604	−0.4006***	−0.1782	−0.4395***	−0.5095***	−0.2018**
HML Devil	0.2232***	0.6035***	0.2880***	−0.3357**	0.3522***	0.0626	0.5707***	0.0499	0.0222	0.2348***
Model 4: FFC										
MKT	1.0309***	1.1489***	1.0439***	1.2957***	0.9955***	0.5474***	0.8673***	0.7334***	0.7565***	0.3128***
SMB	−0.0789	−0.2581***	−0.0707	−0.2519	0.0016	−0.3892***	−0.2460*	−0.3869***	−0.5591***	−0.1693
HML	0.1346	0.7626***	0.3345***	−0.8537***	0.2811*	0.2799***	0.3363***	0.1675	−0.0565	0.2836**
MOM	−0.1459**	−0.1531**	−0.0999	−0.2076**	−0.1025	0.0665	0.0113	0.1043	−0.0286	0.112
Model 5: FFPS										
MKT	1.1071***	1.2477***	1.0673***	1.3430***	1.0918***	0.5309***	0.7585***	0.7158***	0.7627***	0.2917***
SMB	−0.0955	−0.1983*	−0.0778	−0.162	−0.0152	−0.3223***	−0.1421	−0.3771***	−0.5812***	−0.1487
HML	0.1867**	0.8038***	0.3570***	−0.6883***	0.4395***	0.2975***	0.4048***	0.1599	−0.103	0.3436***
LIQ	−0.0905	−0.1352*	−0.0337	−0.0027	0.2939***	0.0307	0.4712***	−0.1347	0.0357	0.0431

Table 5. The table reports coefficients estimates from time series regressions of three different factor models: the Fama and French (2015) five-factor (FF5) model, Model 6; the four-factor (FF4) model that excludes the value factor from the FF5 model, Model 7; and the Hou, Xue, and Zhang (2015) q-factor (HXZ) model, Model 8. The above-mentioned monthly time series regressions are estimated for ten different industries for quintiles 0.10 (a) and 0.90 (b), using their monthly stock returns as our depended variable. The t-statistics adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level respectively.

(a)

Time series Regressions: Three Different Models-Ten Different Industries Returns (Quintile 0.10)										
Q = 0.10	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 6: FF5										
MKT	1.0949***	1.1195***	1.0819***	1.1446***	1.1384***	0.7731***	0.9627***	0.7442***	1.0483***	0.6505***

Continued

SMB	0.1326	−0.2553***	−0.1510*	−0.0451	0.0926	−0.0981	0.1136	−0.3357***	−0.3012**	−0.2371
HML	0.1451*	1.0144***	0.2773***	−0.5771***	0.3080***	−0.1346	0.2576	−0.2786	−0.2922	−0.0544
RMW	0.3767***	−0.1214	0.0322	−0.4876***	0.4082***	0.5041***	0.3864**	0.2638	0.1174	0.0568
CMA	−0.0506	−0.5243***	−0.0201	−0.5327***	−0.0365	0.5407***	0.3185	0.3500	0.5953**	0.4811
Model 7: FF4										
MKT	1.1419***	1.3902***	1.1448***	1.1213***	1.1313***	0.7428***	0.9403***	0.7728***	0.8756***	0.6077***
SMB	0.1306	−0.1712	0.0145	−0.0526	0.1786*	−0.1273	0.1446	−0.3153***	−0.2656**	−0.2541
RMW	0.4454***	0.3686**	0.3240***	−0.4999***	0.6226***	0.5144***	0.4464**	0.1852	0.0402	−0.0205
CMA	0.0986	0.5401***	0.1770*	−0.9899***	0.1664	0.3682***	0.5500***	0.0336	0.0636	0.3986**
Model 8: HXZ										
MRP	1.0503***	1.3737***	1.1089***	1.2786***	1.1136***	0.6283***	0.8523***	0.7894***	0.8363***	0.6759***
ME	0.0006	0.0031***	0.0007	−0.0014	0.0013	0.0009	0.0029**	−0.0014	−0.0019	0.0009
IA	−0.0017	0.0059***	0.0016	−0.0089***	0.0013	0.0009	0.0019	−0.0004	−0.0006	0.0012
ROE	0.0003	0.0049***	0.0022**	−0.0032**	0.0028**	0.0045***	0.0018	0.0040**	0.0006	0.0043*

(b)

Time series Regressions: Three Different Models-Ten Different Industries Returns (Quintile 0.90)

Q = 0.90	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 6: FF5										
MKT	1.1403***	1.2520***	1.1624***	1.1379***	1.1444***	0.7742***	0.8815***	0.8548***	0.7692***	0.3961***
SMB	0.0207	−0.2936**	0.0043	−0.3078	0.0431	−0.1817***	−0.2539	−0.3880***	−0.5036***	−0.1045
HML	0.0988	0.8043***	0.1888***	−0.2935	0.0831	−0.3851***	0.2445	−0.1958	−0.3447**	0.1276
RMW	0.2120**	−0.0042	0.3395***	−0.4639*	0.1494	0.7652***	0.1025	0.4277***	0.0095	−0.1022
CMA	−0.0291	−0.0582	0.125	−0.4694	0.5139**	0.6706***	0.0909	0.4716**	0.5555*	0.6325***
Model 7: FF4										
MKT	1.1603***	1.3420***	1.1351***	1.0390***	1.1742***	0.7378***	0.9851***	0.7991***	0.7725***	0.4004***
SMB	0.0242	−0.176	0.0086	−0.2548	−0.014	−0.2107**	−0.2115	−0.4288***	−0.4934***	−0.1004
RMW	0.2546***	0.3516***	0.3297***	−0.5514***	0.1706	0.5766***	0.3363*	0.3834***	−0.044	−0.0699
CMA	0.0636	0.6934***	0.3029***	−0.8444***	0.5633***	0.3660***	0.3766*	0.2143	0.0725	0.7808***
Model 8: HXZ										
MRP	1.0094***	1.3133***	1.1075***	1.3359***	1.1220***	0.7065***	0.7337***	0.7237***	0.5980***	0.3090***

Continued

ME	−0.0009	−0.0014	−0.0004	−0.0058***	0.0007	−0.0006	−0.001	−0.0030***	−0.0029***	0.0004
IA	0.0013	0.0067***	0.0029*	−0.0038	0.0067***	0.0045***	0.0021	0.0018	0.0046**	0.0047***
ROE	−0.0014	0.0019	0.0025*	−0.0066***	0.0004	0.0059***	−0.0007	0.0051***	−0.0023	−0.0002

Table 6. The table reports coefficients estimates from time series regressions of two different factor models: the Barillas and Shanken (2018) six-factor (BS6) model, Model 9; and the Stambaugh and Yuan (2017) four-factor (SY4) model, Model 10. The above-mentioned monthly time series regressions are estimated for ten different industries for quintiles 0.10 (a) and 0.90 (b), using their monthly stock returns as our depended variable. The t-statistics adjusted for autocorrelation and heteroskedasticity based on the Newey-West methodology. *, **, *** denotes statistical significance at the 10%, 5%, and 1% level respectively.

(a)

Time series Regressions: Two Different Models-Ten Different Industries Returns (Quintile 0.10)										
Q = *0.10*	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 9: BS6										
MKT	0.9962***	1.3523***	1.1187***	1.1277***	1.2335***	0.7031***	0.8661***	0.7860***	0.8005***	0.6137***
SMB	0.0392	−0.1755**	−0.0409	0.1558	−0.0001	−0.1583	0.0507	−0.3743***	−0.3782***	−0.1655
IA	−0.0009	−0.0019	0.0012	−0.0016	0.0032	0.0010	−0.0020	0.0015	−0.0013	−0.0012
ROE	0.0020**	0.0042***	0.0028***	−0.0034**	0.0048***	0.0051***	0.0028	0.0025	−0.0012	0.0021
HML Devil	0.0576	0.6564***	0.1916**	−0.8734***	0.2263	0.1790	0.6597***	−0.2573	0.2394	0.5515***
MOM	−0.1918***	0.1082	−0.0109	−0.3904***	−0.1141	0.0261	0.3149***	−0.1986	0.2181	0.3814***
Model 10: SY4										
MKT	1.0819***	1.1959***	1.1585***	1.2155***	1.1447***	0.7123***	0.8475***	0.8353***	112.920	0.6908***
SMBm	−0.1148	−0.2461***	−0.1398	0.0378	−0.1581	−0.1779	−0.0429	−0.4741***	−1.9944***	−0.2942
MGMT	−0.0109	0.5068***	0.3299***	−0.6953***	0.2185	0.2785***	0.1764	0.0393	0.2046***	0.0980
PERF	−0.0588	−0.3841***	−0.0828	0.0419	−0.0362	0.2008***	−0.0491	0.1463	0.3159	0.1649

(b)

Time series Regressions: Two Different Models-Ten Different Industries Returns (Quintile 0.90)										
Q = *0.90*	Consumer Discretionary	Financials	Industrials	Information Technology	Materials	Consumer Staples	Energy	Health Care	Telecom. Services	Utilities
Model 9: BS6										
MKT	1.0155***	1.2347***	1.1285***	1.2900***	1.0869***	0.7025***	0.7875***	0.6924***	0.6774***	0.3225***
SMB	−0.0866	−0.1236	−0.0498	−0.3847*	0.1243	−0.1387*	−0.2996*	−0.3445***	−0.4767***	−0.1394
IA	−0.0002	0.0032	0.0004	0.0005	0.0054**	0.0026**	−0.0004	0.0023	0.0024	0.0018
ROE	0.0001	0.0052***	0.0033***	−0.0066**	0.0028	0.0080***	−0.0018	0.0048***	−0.0029	−0.0003**

Continued

HML Devil	0.1514	0.5774***	0.3208***	−0.7189***	0.2119	0.0887	0.4570***	0.0521	0.0175	0.4438***
MOM	−0.0733	−0.0961	−0.0155	−0.3419*	−0.1019	−0.1213	0.2332	−0.097	0.0986	0.2118
Model 10: SY4										
MKT	1.0301***	1.3170***	1.0774***	1.2418***	1.1385***	0.7271***	0.6796***	0.7817***	0.8571***	0.3173***
SMBm	0.003	−0.1635	−0.0575	−0.0611	0.0374	−0.0998	−0.264	−0.3865***	−0.6589***	−0.0127
MGMT	0.1603	0.7911***	0.3460***	−0.5050***	0.3845*	0.3928***	0.0467	0.178	0.1534	0.3582***
PERF	−0.1445	−0.3095***	0.034	0.1566	0.0138	0.2872***	−0.0301	0.1588*	0.2271***	−0.0653

summarize the estimated coefficients for the ten different models. In each Table, (a) reports estimated coefficients under quantile 0.10 (recession periods), while (b) under quantile 0.90 (expansion periods).

Quantile regressions (both at the lowest and highest quantiles) do not alter our initial findings. Size factors are negatively related to stock returns of defensive sectors. Momentum remains negative, although weaker in cyclical industries, and both the profitability and the investment risk factors are positively related to subsequent stock returns. Still HXZ's factors perform weaker relatively to those of the FF models, especially in the case of the investment risk factor. LIQ exhibits an even weaker explanatory power in both classifications. Value risk factors are positively related and statistically significant only in cyclical industries, except for the Energy sector under FF construction options. MGMT remains a strong determinant mainly for the stock returns of cyclical industries, whereas PERF is mainly statistically insignificant. Any special considerations either on industry-specific basis or factor behavior are also consistent with our baseline results.

4. Conclusion

Asset pricing literature has documented over 450 predictive factors leading to a "a zoo of factors" (Cochrane, 2011). A stream of papers replicates many published factors to analyze the cross-section of predictors (Green et al., 2017; Hou et al., 2020; Feng et al., 2020). Jensen et al. (2021) argue that replication is the key in validating factors' existence on the same data and sample period as well as, for other time periods and samples.

The present paper builds on this notion. We investigate the return predicting power of ten different asset pricing models over ten different U.S. sector stock returns movements, using both OLS and quantile regressions. Our empirical analysis serves as a profiling study of which factors drive sector indices stock returns, conditional their classification into cyclical and non-cyclical sectors, as well as among "competing factors" (that is factors representing the same form of risk under different constructing choices) which factor prevails. In addition, we also provide inferences on why statistically significant risk factors exhibiting an-off pattern behavior are indeed important.

Industry classification into cyclical and defensive sectors reveals that there are specific patterns, in terms of risk factors' coefficients and statistical significance, within each classification. This finding suggests that sectors might be, at least to some extent, homogenous, within industry classification. However, four sectors exhibit an off-pattern behavior. These industries are Finance, Information Technology, Consumer Staples, and Energy. Hence from an investment perspective, it is important to pay special attention to the risk-return characteristics of these sectors.

In terms of "competing" factors, our analysis reveals that the FF factors overpower the "competing" factors constructed either by Asness and Frazzini (2013) or by HXZ. However, the FF HML factor seems to strongly interact with RMW and CMA (Fama & French, 2015). Furthermore, HXZ's investment factor is strongly influenced by HML Devil, since its explanatory power has diminished.

The momentum risk factor exhibits its weakest performance when the HML Devil, the investment and profitability risk factors are incorporated. In respect to newly introduced risk factors, namely the MGMT factor and the PERF factor proposed by Stambaugh and Yuan (2017), we observe that the former is superior to the latter. Finally, quantile regressions provide qualitatively similar results to those of OLS regressions in respect to coefficient signs and statistical significance of asset pricing factors suggesting that our initial inferences are robust across extreme quintiles.

Declarations

The paper has not been previously published, in English or another language.

The paper is the work of all and only the listed authors.

The work is original and all the work of others is appropriately acknowledged.

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Conflicts of Interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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