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## Research article

## Mispricing and the five-factor model under different market sentiments

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## ABSTRACT

A parsimonious two-factor model consisting of the market factor and the mispricing factor (UMO) yields superior performance in explaining average stock returns than the Fama-French five-factor in high-sentiment periods. However, the five-factor model remains a powerful tool in asset pricing during low-sentiment periods. This is due to the relative importance of risk and mispricing in determining stock prices over different sentiment regimes. Thus, market sentiment should be considered when choosing pricing models.

## 1. Introduction

Motivated by the dividend discount valuation model, Fama and French (2015) introduce profitability and investment factors to their well-known three-factor model (Fama and French, 1993). As more factors are added, one might start to question whether the five-factor model can remain parsimonious. Walkshäusl (2016) argues that a parsimonious two-factor model comprising of the misvaluation/mispricing factor (UMO) and the market factor (MKT) perform at least on par with the new five-factor model and in some instances better. Strikingly, he shows that UMO alone can render all factors in the new five-factor model insignificant except for the market factor. However, little explanation was given. Our study aims to continue this discussion and investigate whether the Fama and French five-factor model actually has little value in the presence of the two-factor model proposed by Walkshäusl (2016).

Hirshleifer and Jiang (2010) construct a zero-investment portfolio, UMO (undervalued minus overvalued), by going long on repurchase stocks and short on the new issue stocks. They claim that this portfolio is the misvaluation factor that captures the behaviour of stock returns left unexplained by traditional risk factors. Therefore, one natural avenue to further our discussion is to expand into the field of behavioural finance. Departing from traditional rational asset pricing, behavioural economists

argue that investor sentiment is unpredictable which can drive stock prices away from fundamental values (De Long et al., 1990). Using the investor sentiment index proposed by Baker and Wurgler (2006), Yu and Yuan (2011) show that a positive mean-variance trade-off exists only in low-sentiment periods.<sup>1</sup> Stambaugh et al. (2012) document that mispricing, in the presence of short-selling, is more prevalent when investor sentiment is high.<sup>2</sup> During high-sentiment periods, optimistic investors tend to over-value stocks while pessimistic investors are unable or unwilling to trade against these optimistic views due to higher arbitrage risk or short sell constraints. As a result, stocks are more likely to be overpriced. On the other hand, during low-investor sentiment periods, the most optimistic investors are likely to be rational investors. When the pessimistic investors are unable or unwilling to sell short, it is less likely to see underpricing during low-sentiment periods. Stambaugh, Yu and Yuan (2012) provide empirical evidence that mispricing is stronger in the periods of high sentiment.

<sup>1</sup> Ho and Hung (2009) find that investor sentiment, as conditioning information in conditional asset pricing models, helps to capture asset pricing anomalies.

<sup>2</sup> Shleifer and Vishny (1997) demonstrate various possible reasons for the limit on short selling, including mutual fund charter simply prohibits it, high shorting costs and the short selling risks. Barber and Odean (2008) show that only 0.29% of positions of individual investors are short positions.

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**Table 1.** Summary statistics for monthly factor returns and the sentiment index. July 1972 to. June 2015 (516 months).

	MKT	SMB	HML	RMW	CMA	UMO	SENT
<b>Panel A1: Premiums (%) and the sentiment index (All)</b>							
Mean	0.53	0.21	0.39	0.27	0.35	0.85	0.001
Std	4.58	3.04	2.94	2.31	1.99	3.06	0.90
<i>t</i> -statistic	2.55	1.54	2.83	2.45	3.78	5.89	0.02
<b>Panel A2: Premiums (%) and the sentiment index (Bearish)</b>							
Mean	0.71	0.39	0.10	-0.05	0.27	0.52	-0.64
Std	4.70	3.05	2.75	1.89	1.79	2.63	0.70
<i>t</i> -statistic	2.29	2.06	0.55	-0.36	2.20	3.06	-10.59
<b>Panel A3: Premiums (%) and the sentiment index (Bullish)</b>							
Mean	0.36	0.02	0.68	0.58	0.43	1.19	0.65
Std	4.45	3.02	3.09	2.63	2.17	3.41	0.54
<i>t</i> -statistic	1.27	0.11	3.43	3.36	3.11	5.19	13.97
<b>Panel B: Correlations</b>							
	MKT	SMB	HML	RMW	CMA	UMO	
SMB	0.24						
HML	-0.28	-0.09					
RMW	-0.25	-0.37	0.14				
CMA	-0.39	-0.06	0.69	0.04			
UMO	-0.49	-0.14	0.59	0.35	0.63		
SENT	-0.04	-0.07	0.08	0.19	0.06	0.1	

Panel A reports the mean, standard deviation and *t*-statistics on the factors and the sentiment index. These *t*-statistics are [Newey and West \(1987\)](#) adjusted. Panel A1 includes all periods. Panel A2 (A3) reports only on the bearish (bullish) periods where the sentiment index is below (above) the median. Panel B reports the correlations among the factor returns and the sentiment index.

Motivated by the aforementioned literature, we conjecture that the mispricing factor should have stronger explanatory power over stock returns during high-sentiment periods. During this period, sentiment traders are more active in the market, and the mean-variance trade-off relationship is relatively weak. However, during low-sentiment periods when the market is relatively more rational due to lower market participation of sentiment traders and a stronger positive mean-variance relation, traditional risk factors, such as the Fama-French five factors, will find their relevance in explaining returns again. If our conjecture is correct, we should expect to observe that the parsimonious model containing UMO significantly outperforms the FF five-factor model in high-sentiment periods. On the other hand, when the market-wide sentiment is low, the FF five-factor model should exhibit stronger explanatory power for stock returns than the parsimonious model. Thus, the benefits of keeping asset pricing models parsimonious without knowing the state of the market sentiment should be marginal if any. In the end, selection between these two types of pricing model should be state dependent. This is exactly what our empirical results suggest.

## 2. Data and summary statistics

Our test assets include the 25 stock portfolios sorted by firm characteristics (i) size and book-to-market ratio, (ii) size and operating profitability, and (iii) size and investment, respectively. We use monthly value-weighted returns of the stock portfolios spanning from July 1972 to June 2015.<sup>3</sup> The FF five-factors: the market factor (MKT), size (SMB, small minus big), book-to-market (HML, high minus low), profitability (RMW, robust minus weak), and investment (CMA, conservative minus aggressive) are obtained from the Kenneth French's website.<sup>4</sup> The UMO factor and investor sentiment index are publicly

<sup>3</sup> Our sample period is just one year longer than the one used by [Walkshäusl \(2016\)](#) for the ease of comparison.

<sup>4</sup> We would like to thank the authors for providing the stock portfolio data and risk factors.

available at Danling Jian's website and Jeffrey Wurgler's website, respectively.<sup>5,6</sup>

Panel A1 of [Table 1](#) reports the summary statistics for the sentiment index and factor returns. Over our sample period, the average market premium amounts to 0.53% per month (*t*-statistic = 2.55). Note that our sample period virtually overlaps with the one used in [Walkshäusl \(2016\)](#). Therefore, our summary statistics closely resemble his [Table 1](#). However, we observe contrasting statistics in Panels A2 and A3 when we split the periods into bearish and bullish periods by following [Stambaugh et al. \(2012\)](#). A month is deemed to be a bearish/low-sentiment (bullish/high-sentiment) period when the associated monthly sentiment index is below (above) the median. Panel A2 shows that the average market premium per month, 0.71%, is economically and statistically significant (*t*-statistic = 2.29) during bearish periods while this premium is not statistically different from zero during the bullish periods. This result is consistent with the argument that investors are more sensitive to risk during low-sentiment periods. Individual investors or noise traders are less likely to participate in the stock market during low-sentiment periods ([Yu and Yuan, 2011](#); [Karlsson et al., 2009](#)). Therefore, investors would request higher compensation for bearing risk in low-sentiment periods ([Baker and Wurgler, 2006](#)). In a similar spirit, [Yu and Yuan \(2011\)](#) find that the correlation between the market's expected return and its conditional volatility is positive during low-sentiment periods and nearly flat during high-sentiment periods.

Sentiment does not only affect the market factor (MKT), Panels A2 and A3 show the monthly premiums on other factors also vary in these

<sup>5</sup> The UMO factor was retrieved from <https://sites.google.com/site/danlingjiang/data-library>. The sentiment index was obtained from <http://people.stern.nyu.edu/jwurgler/>. We would like to thank them for sharing their valuable data.

<sup>6</sup> The sentiment index used is SENT<sup>+</sup> - which is the main sentiment proxy orthogonalized with respect to a set of six macroeconomic indicators ([Baker and Wurgler, 2006](#)).

two sentiment regimes. This suggests that these factors might not have the same effects on stock returns when the market sentiment is different. The misvaluation factor, UMO, has a higher premium during bullish periods (1.19 vs. 0.52). This is consistent with recent sentiment literature findings. For example, Yu and Yuan (2011) report that there is a two-regime pattern on the relationship between risk and return. They argue that there are more sentiment-driven traders during high-sentiment periods. These investors are more inexperienced and

naive. As a result, they have less understanding of the relationship between risk and return. Following this line of argument, we expect UMO to be higher during bullish periods as mispricing is stronger and more prevalent during these high-sentiment periods in the presence of limits on short selling (Stambaugh et al., 2012).

Panel B of Table 1 reports the correlations among the factor returns and the sentiment index. The correlation table shows that factors can be correlated. Therefore, it is necessary to further test whether each factor

**Table 2.** Using five factors in regressions to explain monthly returns on the sixth.

Regression Dependent	Panel A: All Period					
	(1) UMO	(2) MKT	(3) SMB	(4) HML	(5) RMW	(6) CMA
Intercept	0.53 (4.98)	1.10 (6.10)	0.20 (1.54)	-0.15 (-1.31)	0.16 (1.75)	0.11 (1.49)
MKT	-0.15 (-4.62)		0.12 (2.61)	0.05 (1.22)	-0.04 (-1.53)	-0.06 (-3.18)
SMB	0.06 (1.13)	0.23 (2.55)		-0.02 (-0.41)	-0.23 (-2.93)	0.00 (-0.12)
HML	0.26 (3.80)	0.18 (1.29)	-0.05 (-0.41)		0.03 (0.34)	0.32 (10.77)
RMW	0.36 (4.06)	-0.15 (-1.41)	-0.47 (-3.77)	0.04 (0.34)		-0.16 (-3.56)
CMA	0.56 (5.50)	-0.54 (-3.07)	-0.01 (-0.12)	0.81 (9.77)	-0.37 (-3.66)	
UMO		-0.54 (-4.99)	0.11 (1.14)	0.26 (3.59)	0.34 (5.25)	0.22 (6.79)
R <sup>2</sup>	0.57	0.28	0.16	0.52	0.28	0.59
	Panel B: Bearish Period					
Intercept	0.48 (3.70)	0.89 (3.65)	0.25 (1.35)	-0.33 (-2.21)	0.03 (0.29)	0.22 (2.36)
MKT	-0.10 (-2.24)		0.20 (3.42)	0.04 (0.71)	-0.08 (-2.66)	-0.08 (-3.33)
SMB	-0.01 (-0.13)	0.42 (3.94)		0.11 (1.60)	-0.04 (-0.98)	-0.01 (-0.43)
HML	0.39 (4.81)	0.16 (0.74)	0.22 (1.70)		-0.14 (-2.04)	0.26 (5.83)
RMW	0.46 (3.71)	-0.54 (-2.67)	-0.13 (-0.98)	-0.24 (-2.22)		-0.33 (-4.40)
CMA	0.32 (2.80)	-0.77 (-3.23)	-0.06 (-0.43)	0.63 (5.65)	-0.47 (-3.91)	
UMO		-0.37 (-2.37)	-0.02 (-0.13)	0.36 (4.87)	0.25 (4.14)	0.12 (3.23)
R <sup>2</sup>	0.36	0.25	0.14	0.45	0.33	0.47
	Panel C: Bullish Period					
Intercept	0.66 (4.54)	1.31 (5.15)	0.36 (1.76)	0.15 (0.98)	0.22 (1.63)	-0.12 (-1.43)
MKT	-0.18 (-5.26)		-0.01 (-0.11)	-0.03 (-0.86)	-0.01 (-0.14)	-0.02 (-0.66)
SMB	0.04 (0.69)	-0.01 (-0.11)		-0.17 (-2.79)	-0.35 (-3.34)	0.05 (1.86)
HML	0.09 (1.10)	-0.12 (-0.86)	-0.33 (-3.04)		0.12 (0.88)	0.33 (10.94)
RMW	0.27 (3.25)	-0.02 (-0.14)	-0.53 (-4.70)	0.09 (0.94)		-0.08 (-2.43)
CMA	0.86 (6.93)	-0.16 (-0.66)	0.26 (1.79)	0.88 (8.46)	-0.29 (-2.28)	
UMO		-0.67 (-5.13)	0.08 (0.68)	0.09 (1.04)	0.35 (3.78)	0.32 (9.50)
R <sup>2</sup>	0.72	0.39	0.29	0.65	0.38	0.74

This table shows results from regressing each of the six factors on the other five factor over the sample period. Dependent indicates the dependent variables in the regression. Bearish (bullish) periods are when the sentiment index is below (above) the median. Newey and West (1987) adjusted *t*-statistics for the coefficients are given in parentheses. R<sup>2</sup> is adjusted for degrees of freedom.

**Table 3.** The chosen factor models and their explanatory power over the redundant factors.

Regression Dependent	Panel A: Bearish Period		Panel B: Bullish Period			
	(1) SMB	(2) RMW	(1) SMB	(2) HML	(3) RMW	(4) CMA
Intercept	0.24 (1.35)	0.02 (0.21)	0.22 (1.11)	0.02 (0.13)	0.18 (1.26)	-0.12 (-1.11)
MKT	0.21 (3.67)	-0.09 (-3.06)	0.01 (0.10)	-0.07 (-1.80)	-0.01 (-0.15)	-0.04 (-1.49)
UMO	-0.05 (-0.43)	0.25 (4.10)	-0.17 (-2.17)	0.57 (8.11)	0.34 (4.61)	0.47 (12.09)
HML	0.24 (1.93)	-0.14 (-2.26)				
CMA	0.00 (-0.01)	-0.47 (-3.91)				
R <sup>2</sup>	0.14	0.33	0.03	0.48	0.19	0.63
	R <sup>2</sup> = 0.23, GRS = 0.89, p (GRS) = 0.41		R <sup>2</sup> = 0.33, GRS = 1.71, p (GRS) = 0.15			

This table has two panels. Panel A (B) reports the results from regressing the two (four) redundant factors on the selected four (two) factors during the bearish (bullish) periods. Bearish (bullish) periods are when the sentiment index is below (above) the median. The statistical inference is based on Newey and West (1987) adjusted *t*-statistics. R<sup>2</sup> provides the average regression R<sup>2</sup> value, adjusted for degrees of freedom, across the test portfolios. GRS is the statistic of Gibbons et al. (1989) testing the null hypothesis that the intercept estimates are jointly zero across a given set of test portfolios. p(GRS) is the *p*-value of GRS.

holds unique information using the factor redundancy tests. However, we argue that this should be done separately for the bearish and the bullish periods. Although Panel B shows that sentiment does not have a high correlation with other factors, it does have an impact on how these factors behave as shown in Panel A.

### 3. Factor redundancy tests

In this section, we perform the factor redundancy tests by following Fama and French (2016). The objective is to test whether each factor holds unique information that cannot be explained by the other factors. To test for redundancy, we regress each of the factors on all the other factors. If the intercept is not significantly different from zero, this factor is redundant. Fama and French (2016) argue that this test has a definitive nature – a factor adds nothing to the model's explanatory power over return if this factor is found to be redundant. As a result, redundant factors should be dropped from the regression.

Table 2 presents the factor redundancy test results in all periods (Panel A), bearish periods (Panel B) and bullish periods (Panel C). Panel A results are virtually the same as those reported in Walkshäusl (2016). Only UMO and MKT have unique information when we consider the entire sample period. However, the story changes when we consider only bearish periods. Panel B of Table 2 shows that SMB and RMW now become redundant. This suggests a four-factor model (MKT, HML, CMA and UMO) is appropriate during bearish periods. Panel C of Table 2 is again suggesting a parsimonious two-factor (MKT and UMO) model similar to Panel A. This indicates that the market factor and the mispricing factor alone can explain variations of returns during the bullish markets. To confirm our chosen model, we will regress these redundant factors on our chosen factors.

Table 3 Panel A (B) reports the results from regressing the two (four) redundant factors on the selected four (two) factors during the bearish (bullish) periods. During the bearish periods, the two redundant factors are SMB and RMW. Panel A of Table 3 reports that both have no residual explanatory power in the presence of the chosen four-factor model because the two intercepts are statistically insignificant. We also perform the GRS test (Gibbons et al., 1989) to examine whether all of the intercept estimates are jointly zero. In this case, the GRS is equal to 0.89 for regressions (1) and (2) of Panel A. Thus, we cannot reject the null that both intercepts are equal to zero. Similarly, Panel B results also confirm that the four factors (SMB, HML, RMW and CMA) are redundant.

### 4. Asset pricing tests

In this section, we test the performance of our chosen models against the Fama and French five-factor model and the two-factor model of Walkshäusl (2016) using the acid test (Fama and French, 1993). This test can shed light on whether these models can explain the cross variations of stock returns. Following Fama and French (2015), we also test three sets of 25 value-weighted portfolios formed on firm size and book-to-market ratio, firm size and operating profitability, and firm size and investment, respectively.

Table 4 reports the regression results on the five-factors, two-factors and four-factors, respectively. Panel A, B and C report on portfolios formed on firm size and book-to-market ratio, firm size and profitability, and firm size and investment respectively. Panel A1, B1 and C1 are for the bearish periods while A2, B2 and C2 are for the bullish periods.

Panel A1 shows that all models perform well for bearish periods. For each model, all 25 intercepts are statistically insignificant, suggesting no return left unexplained by these models. As Walkshäusl (2016) correctly points out, the better way to interpret the results is to benchmark these results using the GRS statistics. Lower GRS indicates better model performance. Based on the GRS figures in Panel A1, the four-factor model performs better than the two-factor model while the five-factor model is the last. This suggests that during bearish periods traditional risk factors should remain in asset pricing models. Examining all the bearish period results (Panel A1, B1 and C1), we find that this is indeed the case. Traditional risk factors are highly relevant, and the four-factor models take the lead in all the bearish periods based on the GRS statistics. Fama and French five-factor can even overtake the two-factor model during bearish periods when portfolios are formed on firm size and profitability (Panel B1). This is in stark contrast to Walkshäusl (2016) but consistent with our expectation.

Based on the factor redundancy tests reported in the previous section, our chosen model for bullish periods is also the two-factor model (MKT and UMO). Panel A2 shows that the two-factor model can explain 23 out of the 25 portfolios while the five-factor model can only explain 15 out of the 25 portfolios. Note the significant intercepts are bolded which implies the corresponding portfolio has an unexplained component left. GRS also confirms the superior performance of the two-factor model. This finding is persistent no matter how we form the portfolios (Panel A2, B2 and C2). As expected, all bullish period results show the two-factor model outperforms the five-factor model.

**Table 4.** Time-series regressions to explain monthly test portfolio returns.

	Five-Factor Model					Two-Factor Model (MKT UMO)					Four-Factor Model (MKT HML CMA UMO)				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
<b>Panel A1: Formed on Firm Size and Book-to-Market (Bearish Period)</b>															
Small	-0.21	0.06	-0.03	0.11	0.06	0.22	0.38	0.16	0.21	0.12	0.15	0.39	0.19	0.30	0.23
2	-0.04	-0.10	-0.05	-0.09	-0.17	0.29	0.15	0.13	0.00	-0.13	0.23	0.17	0.20	0.10	0.05
3	0.00	-0.04	-0.07	0.07	-0.02	0.19	0.09	0.05	0.11	0.09	0.17	0.12	0.12	0.20	0.18
4	0.05	-0.13	-0.08	0.06	-0.12	0.22	0.00	-0.01	0.08	-0.11	0.15	-0.01	0.01	0.15	-0.02
Big	0.05	-0.03	0.04	-0.20	0.08	0.03	-0.01	-0.01	-0.34	-0.09	-0.01	-0.04	-0.01	-0.18	0.10
	R <sup>2</sup> = 0.93, GRS = 1.30, p (GRS) = 0.16					R <sup>2</sup> = 0.79, GRS = 1.01, p (GRS) = 0.46					R <sup>2</sup> = 0.83, GRS = 0.88, p (GRS) = 0.64				
<b>Panel A2: Formed on Firm Size and Book-to-Market (Bullish Period)</b>															
Small	<b>-0.47</b>	<b>0.30</b>	0.04	<b>0.31</b>	<b>0.21</b>	-0.17	0.42	0.22	0.38	0.41					
2	-0.17	0.01	-0.07	0.13	-0.01	0.16	0.31	0.24	0.39	0.21					
3	0.14	0.01	-0.16	<b>-0.19</b>	0.01	<b>0.40</b>	0.20	0.12	0.06	0.33					
4	<b>0.31</b>	<b>-0.29</b>	<b>-0.34</b>	-0.06	-0.22	<b>0.33</b>	-0.10	-0.19	0.02	0.02					
Big	0.13	-0.08	<b>-0.22</b>	<b>-0.39</b>	-0.17	0.07	-0.06	-0.17	-0.22	-0.07					
	R <sup>2</sup> = 0.90, GRS = 4.13, p (GRS) = 0.00					R <sup>2</sup> = 0.72, GRS = 2.34, p (GRS) = 0.00									
<b>Panel B1: Formed on Firm Size and Profitability (Bearish Period)</b>															
Small	0.05	0.02	-0.03	0.07	-0.04	0.34	0.14	0.06	0.18	0.14	0.31	0.23	0.15	0.31	0.22
2	0.08	-0.13	-0.04	-0.09	-0.04	0.35	0.05	0.05	0.05	0.17	0.32	0.09	0.16	0.17	0.25
3	0.19	-0.10	0.01	-0.07	0.01	0.35	0.04	0.11	0.04	0.14	<b>0.36</b>	0.07	0.16	0.11	0.20
4	0.16	-0.07	-0.13	0.04	-0.13	0.31	0.06	-0.07	0.14	-0.04	0.23	0.01	-0.01	0.16	-0.02
Big	0.12	<b>-0.18</b>	0.07	-0.01	0.06	-0.03	-0.19	0.06	-0.06	0.04	0.00	<b>-0.21</b>	0.00	-0.06	0.02
	R <sup>2</sup> = 0.94, GRS = 1.09, p (GRS) = 0.35					R <sup>2</sup> = 0.81, GRS = 1.24, p (GRS) = 0.21					R <sup>2</sup> = 0.83, GRS = 1.02, p (GRS) = 0.44				
<b>Panel B2: Formed on Firm Size and Profitability (Bullish Period)</b>															
Small	-0.26	0.11	-0.08	-0.15	-0.26	-0.13	0.32	0.16	0.19	0.12					
2	<b>-0.25</b>	-0.12	-0.02	0.03	-0.10	-0.02	0.09	0.25	<b>0.43</b>	0.34					
3	-0.02	0.05	-0.05	-0.13	-0.05	0.08	0.18	0.14	0.22	0.33					
4	0.07	0.15	-0.18	-0.11	-0.06	0.02	0.11	-0.06	0.04	0.11					
Big	-0.01	-0.02	0.00	0.05	0.05	-0.21	-0.01	0.01	0.07	-0.03					
	R <sup>2</sup> = 0.92, GRS = 1.81, p (GRS) = 0.01					R <sup>2</sup> = 0.77, GRS = 1.41, p (GRS) = 0.10									
<b>Panel C1: Formed on Firm Size and Investment (Bearish Period)</b>															
Small	0.23	0.14	0.11	-0.03	<b>-0.23</b>	0.50	0.31	0.22	0.16	0.03	0.46	0.35	0.30	0.20	0.11
2	-0.04	-0.09	0.03	-0.08	-0.05	0.19	0.11	0.20	0.04	0.19	0.17	0.13	0.23	0.16	0.24
3	0.08	0.11	-0.04	0.03	0.01	0.26	0.29	0.06	0.10	0.12	0.24	<b>0.29</b>	0.09	0.20	0.20
4	-0.05	-0.12	-0.03	0.04	0.06	0.16	-0.03	0.07	0.09	0.14	0.08	-0.04	0.07	0.11	0.17
Big	-0.03	-0.07	-0.07	0.05	<b>0.20</b>	0.10	0.00	-0.07	-0.06	-0.01	-0.09	-0.12	-0.08	-0.03	0.10
	R <sup>2</sup> = 0.94, GRS = 1.50, p (GRS) = 0.07					R <sup>2</sup> = 0.82, GRS = 1.39, p (GRS) = 0.11					R <sup>2</sup> = 0.84, GRS = 1.2, p (GRS) = 0.24				
<b>Panel C2: Formed on Firm Size and Investment (Bullish Period)</b>															
Small	0.22	<b>0.24</b>	<b>0.28</b>	0.07	<b>-0.51</b>	0.20	0.34	0.42	0.24	-0.14					
2	-0.05	-0.01	<b>0.23</b>	0.10	<b>-0.22</b>	0.06	0.25	0.35	<b>0.41</b>	0.21					
3	-0.03	0.08	0.02	0.07	0.00	0.14	0.18	0.18	0.22	<b>0.37</b>					
4	<b>-0.24</b>	-0.08	-0.02	0.01	<b>0.27</b>	-0.14	0.02	-0.03	0.05	<b>0.36</b>					
Big	0.01	-0.02	-0.04	-0.01	0.10	0.02	-0.03	-0.06	-0.15	0.09					
	R <sup>2</sup> = 0.92, GRS = 3.40, p (GRS) = 0.00					R <sup>2</sup> = 0.76, GRS = 2.48, p (GRS) = 0.00									

This table reports the models' estimated intercepts over the sample period. Intercepts that are statistically distinguishable from zero at the 5% level of significance or better are bolded. The statistical inference is based on [Newey and West \(1987\)](#) adjusted t-statistics. R<sup>2</sup> provides the average regression R<sup>2</sup> value, adjusted for degrees of freedom, across the test portfolios. GRS is the statistic of [Gibbons et al. \(1989\)](#) testing the null hypothesis that the intercept estimates are jointly zero across a given set of test portfolios. p(GRS) is the p-value of GRS. Bearish (bullish) periods are when the sentiment index is below (above) the median.

### 5. Conclusions

The Fama and French five-factor model has been widely adapted by researchers and practitioners. Yet, with this introduction of two extra factors over the original FF model, some fear that more and more factors will be added to our pricing models. Thus, researchers begin to investigate the possibility of a simpler yet equally powerful model. [Walkshäusl \(2016\)](#) documents that his parsimonious two-factor model (market and mispricing) remarkably outperforms the Fama and French five-factor model in many cases while it is at least on par with the five-factor model in the other cases. Yet, little explanation was given as to why this two-factor model outperforms.

Here, we carefully consider the reason for the success of this newly proposed model. This model is essentially a standard CAPM model with an additional mispricing factor (UMO). As mispricing is designed to capture price variation unexplained by traditional factors, it is natural to bring the behaviour dimension to our discussion. Therefore, our study assesses the performance of these models by considering the link between market sentiment, risk, mispricing, and stock returns. Adopting a similar sample period and testing methodologies, we find that this two-factor model only significantly outperforms the five-factor model while the market sentiment is high and bullish. Interestingly, the two-factor model actually underperforms during the low-sentiment periods. This is consistent with the market sentiment literature which argues that there

are more overpricing during high-sentiment periods and markets are relatively more rational during low-sentiment periods. Therefore, this mispricing factor (UMO) can explain what cannot be explained by traditional factors only during the bullish periods but not during bearish periods. In this case, despite facing the challenge of the parsimonious two-factor model, the FF five-factor model remains to be a valuable pricing model when the mean-variance relation still holds. Overall, our study shows that stock return variations are a complex manifestation of the interaction between risk and mispricing forces. Investors are advised to choose the appropriate factor model during different periods. In addition, our findings also provide further empirical support to recent market sentiment studies that argue there is more mispricing during high-sentiment periods.

### Declarations

#### Author contribution statement

E. Chen and J. Ho: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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