Are Momentum Crashes Individualistic?

Inês Mingatos

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ABSTRACT

According to Chui, Titman, and Wei (2010) momentum returns are higher in more individualistic countries. On the other hand, it is known that the momentum strategy reports significant losses when it experiences crashes, and these crashes happen when stock markets rebound in bear markets. With a sample of 24 countries with different levels of individualism, I created dynamic portfolios based on volatility scaling to predict momentum crashes, to study if momentum crashes and the level of individualism are related. I find the level of individualism of countries and momentum crashes are not correlated, since momentum crashes occur in a similar way in the universe of the countries that I used. The implementation of the dynamic portfolio strategy maintains the evidence that countries with higher level of individualism have better returns than those countries with lower level of individualism. The momentum strategy experiences more significant crashes during post-bear market periods. As a result, it behaves like a short call option on the market with an optionality coefficient.

Author: Inês Jerónimo Mingatos

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RESUMO

Chui, Titman e Wei (2010), propuseram que os retornos do momentum são mais elevados em países com um nível maior de individualismo. Por outro lado, sabe-se que a estratégia de momentum regista perdas significativas quando sofre quedas, e estas quedas acontecem quando há recuperação após um mercado em baixa. Com uma amostra de 24 países com diferentes níveis de individualismo, criei carteiras dinâmicas baseadas no escalamento da volatilidade para prever quebras da estratégia de momentum e para estudar a relação entre as quebras do momentum e o nível de individualismo. O nível de individualismo dos países e as quedas do momentum não estão correlacionados, uma vez que as quedas de momentum ocorrem de forma semelhante em todo o universo de países que utilizei. A implementação da estratégia de carteira dinâmica mantém a evidência de que países com maior nível de individualismo têm melhores retornos do que países com menor nível de individualismo. A estratégia de momentum regista quedas significativas durante os períodos de recuperação pós mercados em baixo. Consequentemente, comporta-se como uma opção de compra curta no mercado com um coeficiente de opcionalidade.

Autor: Inês Jerónimo Mingatos

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1.Introduction

The momentum strategy is one of the most popular investment strategies based on buying assets that have performed well in recent months and selling those that have performed poorly. The returns of the momentum strategy can increase due to various factors, one of which is if the level of individualism of the country in which we are investing is higher. However, even though momentum is one of the most popular investment strategies, it also has its bad moments, called momentum crashes. Daniel, and Moskowitz (2016) studied the effect of momentum crashes for users, noting that although momentum returns are on average positive for most of the time, when the market rebounds after the midst/end of the bear markets the momentum returns start to fall and the losses are significant. These losses are usually associated with momentum crashes, which in turn are associated with market crashes. Linked to these momentum crashes Daniel, and Moskowitz (2016) analyzed momentum crashes in more depth by discovering the optionality effect that momentum returns exhibit during the bear market moments. This is a different outcome than would be expected, since momentum returns underperform when the market is rising after a bear market, acting like a short call option on the market. In this way, momentum returns fall more in these rebalancing periods after a bear market than in a bear market period alone.

Chui, Titman and Wei (2010) studied the effect of each country's level of individualism on momentum returns, using a measure for the level of individualism that comes from the study proposed by Hofstede (2001). Analyzing separately the two works by momentum Daniel, and Moskowitz (2016) and Chui, Titman and Wei (2010) I realized that these two works are quite complete and are two good topics to aggregate and study simultaneously. I decided to study whether there is any relationship between the level of individualism and momentum crashes in a deep form of the optionality coefficient in a sample of 24 countries.

My motivation was to understand how these two factors of individualism and momentum crashes behaved in a diverse sample of countries containing markets with different characteristics. The title of my dissertation is "Are Momentum Crashes Individualistic?", and the reason for choosing this title is the combination of the two factors I decided to study which aims at understanding if momentum crashes are affected by the country's level of individualism. Following the sample period, I used the last 35 years, from 1988:01 to 2023:06. The first objective of this dissertation was to verify the pattern proposed by Chui, Titman and Wei (2010) that countries with a higher level of individualism have better momentum performance (better returns) than countries with a lower level of individualism by checking this pattern for the entire sample of countries for the entire time period. Then I applied the methodology used in the "Momentum Crashes" article regarding the relationship between bear market periods and contemporaneous up-market movements. Adding tests that study the effect of the optionality coefficient vs. the level of individualism in each country and the optionality coefficient vs. momentum returns. As variance is a relevant factor that predicts momentum returns negatively in periods of rebounding after bear markets, I also performed a regression to investigate the effect of variance on my sample. I then constructed the dynamic momentum portfolio, according to work proposed by Barroso and Santa-Clara (2015) and Barroso, Edelen and Karehnke (2018) which proposed that the best approach to controlling momentum crashes is to scale portfolio weights based on the volatility.

Following the Daniel, and Moskowitz (2016) approach to estimate the forecasted realized volatility for the following month, I regress a linear combination of the GJR-GARCH model and the lagged 126-day volatility momentum return. To create the dynamic portfolio, I followed the optimal weights formula, which comes from the optimized portfolio proposed by Markowitz (1952). With the dynamic portfolio built for each of the 24 countries, I aggregated the country data according to their level of individualism and analyzed the differences in relation to the optimal weights that were assigned to see if there was any kind of relation between the optimal weights and the level of individualism.

The last sections of the dissertation are the analyses and construction of two new investment portfolios. Based on the insights gathered in the previous sections, I proposed these new portfolios for both the initial momentum strategy (WML) and the dynamic momentum portfolio. The new investment portfolios result from a strategy of bidding long the returns of countries with a higher level of individualism and shorting the returns of countries with a lower level of individualism, i.e. a momentum strategy based on the level of individualism that influences the portfolio's returns. The optionality coefficient was one of the factors I studied in these new portfolios to see if the behavior changed or remained the same as in the momentum portfolios for each country individually. To finalize the analysis of these new investment portfolios, I constructed a table with the return statistics for both the new High-minus-Low portfolios and the portfolios for each individual level of individualism (High, Medium, Low) for both the initial momentum portfolio and the dynamic momentum portfolio.

2. Literature review

The momentum strategy is based on the performance of past returns to predict future returns, with the assets with the best performance in recent months being the winners and those with the worst returns in recent months being the losers. The strategy is implemented by selling (short) past losers and buying (long) past winners. The momentum strategy (WML) has been studied several times and proven to be robust for different markets, asset classes, and time periods. Jegadeesh and Titman (1993) and Asness (1994) proposed the momentum strategy by sorting companies between 3 and 12 months past returns. Jegadeesh and Titman (1993) proposed the momentum strategy by analyzing its effect on US stock returns, studying the effect of the Momentum strategy between 1965 and 1989. Later, Jegadeesh and Titman (2001) tested the Momentum Strategy for a new period between 1990 and 1998 to the same classes of assets - US common stock returns. As a way of testing the robustness of the momentum strategy Israel and Moskowitz (2013) studied the effect for earlier and later periods between 1927 and 1965 and between 1990 and 2012. Rouwenhorst (1998; 1999) carried out the Momentum study effect for Europe and emerging markets, and Griffin, Ji, and Martin (2003) carried out the study for the rest of the world, presenting the effect of the Momentum Strategies more comprehensively. There are exceptions for some Asian countries, Chui, Titman, and Wei (2003).

Associated with the average solid returns in the momentum strategy are occasional momentum crashes happening worldwide, during the same period. Brunnermeier, Nagel, and Pedersen, (2008) studied the carry trade returns of currencies that behave like momentum strategy returns in times of crashes, which are negatively skewed and negative and usually persistent and pronounced. In this way, Daniel, and Moskowitz (2016) present relevant empirical results for the study of the behavior of momentum crashes in a detailed analysis for the USA. They also study this effect in other countries, but the significant analyses are for the USA. This research ran from 1927:01 to 2013:03 for the universe of all listed NYSE, Amex, or Nasdaq using only the returns of the common shares to create the momentum portfolio (WML), starting by understanding how momentum crashes affect the returns of the WML portfolio. The following fact studied is the behavior of the momentum strategy as a short call option in the market, this effect being due to the losers' portfolio, consistent with Cooper, Gutierrez, and Hameed (2004), who present an in-depth analysis of how momentum returns are inferior when the market is rebalancing. This short call option effect on the market is visible when the market falls, the returns gain a little, but when the market rises, the returns lose a lot. The behavior of the short call option is related to the variation of the volatility because the value of the call option is an increasing function of the value of the volatility, so Daniel, and Moskowitz (2016) study the effect of periods with high volatility on momentum returns. The volatility of the momentum strategy can be predicted in this way, using the GJR-GARCH model proposed by Glosten, Jagannathan, and Runkle (1993) to adjust the weights in the momentum portfolio and create a dynamic portfolio. Taking the insights from the momentum return forecasting study and the fact that the volatility of the momentum strategy is a decreasing function of momentum returns, they created an optimized dynamic momentum strategy for the WML portfolio, adjusting the weights up or down based on an optimal weight function. The optimal weights form helps to conclude that the weights of the WML portfolio are inversely proportional to the predicted volatility of the WML portfolio. The optimal weight used in the strategy comes from the version of the optimized portfolio proposed by Markowitz (1952). Concluding that the optimal dynamic strategy is the constant volatility strategy, which is the strategy proposed by Barroso and Santa-Clara (2015).

Momentum returns are influenced by cultural differences, such as the level of individualism in each country. Chui, Titman, and Wei (2010) studied the effect of each country's individualism on momentum strategy returns. The index of individualism was proposed by Hofstede (2001). This index reflects the degree to which each individual focuses on internal attributes, such as their own abilities, to differentiate themselves from others. The level of individualism comes from a cross-country psychological survey of employee values carried out by Geert Hofstede between 1967 and 1973. The employees surveyed were IBM employees from 72 countries and included more than 88,000 responses. Of the universe of 72 countries, 40 had more than 50 respondents. Only years later were ten more countries added to the sample, thus concluding a universe of 50 countries with a level of individualism. This study was carried out in a universe of 50 countries, with the USA having the highest level of individualism (91) and Indonesia and Pakistan the lowest (14). Chui, Titman, and Wei (2010) also reported a positive relationship between the level of individualism and volatility, as well as the magnitude of momentum returns. Further evidence from this study was that momentum returns are negatively related to volatility.

Harvey and Siddique (2001) proposed that if asset returns have symmetric skewness, their expected returns should include some reward for accepting this risk and thus assessed assets that incorporate this asymmetry. Their results showed that the momentum effect is related to systematic asymmetry. Portfolios with lower returns are associated with higher systematic asymmetry, and portfolios with higher returns are associated with lower systematic asymmetry.

3. Data sources

In this dissertation, the main data source is the AQR data sets, namely the files Betting against Beta: Equity Factors, Daily and Monthly[1]. These files are linked to the original factors used in "Betting Against Beta" by Frazzini and Pedersen (2014). Consistent with Daniel, and Moskowitz (2016), I used each country's Momentum Strategy WML and Excess Market Returns. The extraction of the Momentum WML daily and monthly excess returns by the "UMD" sheet (the momentum factor Up minus Down), the excess market returns by the "MKT" sheet (the market returns in excess risk-free), and the risk-free by the "RF" sheet on the file Betting against Beta: Equity Factors for all countries. All the excess returns of the momentum strategy and excess market returns are in US dollars, so there is an abstraction from exchange rate factors. The risk-free rate used is that of the USA since the study is carried out with all values in dollars and from the perspective of an American investor. The universe of analysis is made up of 24 countries with different levels of individualism between 1988:01 and 2023:06, with some exceptions for Portugal's WML Portfolio data, which only starts in 1988:02, Greece's data in 1988:09 and Israel's data, which starts in 1994:12. With regard to the Excess Market Returns data, although most of the data for the 24 countries is between 1988:01 and 2023:06, there are some exceptions, such as Portugal where the data starts at 1989:05, Greece where it starts at 1989:09, Ireland where the data starts at 1989:01 and runs until 1989:11, starting continuously at 1990:02 and the data for Israel where it starts at 1996:02. The individualism level data for each country is a constant value throughout the sample. The data for the individualism index of the countries was taken from the Hofstede (2001) (the data on each country's level of individualism can be found in Table 1.), I divided the countries into three groups based on their level of individualism: High, Medium and Low. This division is consistent with the paper "Individualism and Momentum around the World" where the sample of countries is divided based on the individualism index, where the top 30% of countries are in the High group and the bottom 30% are in the Low group.

[1] The data can be found in the following link: www.aqr.com/Insights/Datasets

Table 1. Index of Individualism of each country

This table presents the index of individualism and corresponding division of the level of individualism based on the individualism index, where the top 30% of countries are in the High group and the bottom 30% are in the Low group.

Country	Index of individualism	Level of individualism
United States (USA)	91	High
Australia	90	High
United Kingdom (UK)	89	High
Canada	80	High
Netherlands	80	High
New Zealand	79	High
Italy	76	High
Belgium	75	High
Denmark	74	Medium
France	71	Medium
Sweden	71	Medium
Ireland	70	Medium
Norway	69	Medium
Switzerland	68	Medium
Germany	67	Medium
Finland	63	Medium
Austria	55	Low
Israel	54	Low
Spain	51	Low
Japan	46	Low
Greece	35	Low
Portugal	27	Low
Hong Kong	25	Low
Singapore	20	Low

4. Methodology and Empirical Results

This section presents the methodology and empirical results used during the dissertation. Before starting to work on the sample of countries I selected, I replicated part of the results obtained by Daniel, and Moskowitz (2016), replicating only the results I found relevant to my work to adopt the same methodology. The returns of all the portfolios were worked out throughout the programming in numerical format (1.0% = 0.01), and the volatilities and variances were always annualized throughout the analysis. All the results were programmed in Python, as were the figures, while the tables were made in Excel format.

4.1 Momentum Crashes vs Momentum Returns Performance

Following the same approach as Daniel, and Moskowitz (2016), I start by analyzing the differences between momentum returns and the respective momentum crashes but now with larger sample sizes across four countries: two with extremely high levels of individualism (Australia and The United Kingdom) and two with low levels of individualism (Honk Kong and Singapore). The sample of all countries regarding the level of individualism has the USA with the higher value of individualism (91) and Singapore with the lowest value of individualism (20). The average regarding the level of individualism is 64 for the entire sample of 24 countries. Table 1 shows the value of each country's level of individualism. The two countries with a low level of individualism were Singapore and Hong Kong, which have an index level of individualism of 20 and 25, respectively, and these are the two countries in my sample with the lowest level of individualism. Australia and the UK were the other two countries chosen to study the behavior of momentum returns and the respective momentum crashes, as they are the second and third countries with the highest level of individualism, respectively, with 90 and 89 index levels of individualism, of the sample of 24 countries, the USA is the country with the highest level of individualism in the sample.

However, I decided not to report and analyze the results of this country (USA) since Daniel, and Moskowitz (2016) made an in-depth analysis of the USA. It was relevant to show this evidence in the following countries with the highest level of individualism since I intend to verify if the observed pattern remains consistent in a different sample. The Fig 1. shows the results for Australia (Panel D) and the UK (Panel C), these two countries are the ones with high levels of individualism, and it is possible to see a tendency for the returns of the WML portfolio to outperform the market. Although this is not a complete representation of all the countries with high levels of individualism, on average, the momentum strategy returns are higher than those of the market, which is consistent with the literature. This pattern is reversed for countries with a lower level of individualism, and market returns tend to be higher than WML portfolio returns. This pattern is shown in Fig 1, for Hong Kong (Panel A) and Singapore (Panel B), and is consistent with the work proposed by Chui, Titman and Wei (2010). There is an apparent relationship between a country's level of individualism and the performance of the momentum strategy.

Table 2 show the results of a complementary analysis comparing the 15 periods with the worst returns in these countries. Considering the momentum crashes in the graphs of the four countries and their fifteen worst returns, it is possible to see a similarity of crash periods between the more individualistic and less individualistic countries. Another conclusion is that momentum crashes happen simultaneously in all countries, so there is no relationship between a country's level of individualism and the momentum when the momentum crashes happen.

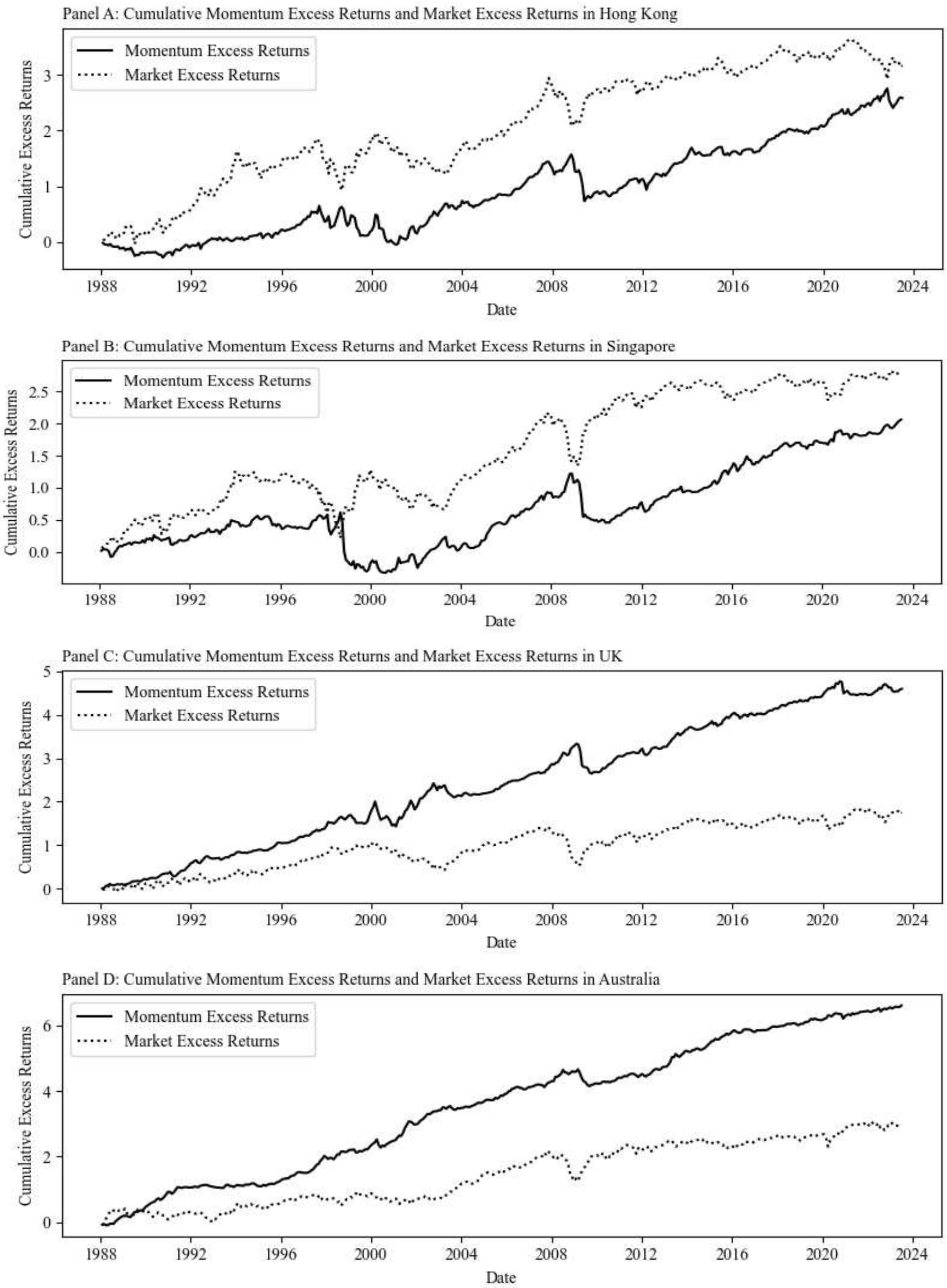

Figure 1. Cumulative Momentum Excess Returns vs. Market Excess Returns in Australia, United Kingdom, Hong Kong, and Singapore.

All the returns shown in the four panels represent the cumulative sum returns of the logarithmic monthly excess returns.

Table 2. The 15 worst monthly momentum excess returns are in Australia, the UK, Hong Kong, and Singapore. This table shows the 15 worst monthly momentum portfolio excess returns for Australia, the UK, Hong Kong, and Singapore between 1988:01 and 2023:06. All results are presented in percentages.

Panel A: Hong Kong		
Year : Month	WML	$E(R_m - r_f)$
2009:05	-28.51%	19.64%
2000:04	-22.87%	-13.96%
2008:12	-21.54%	8.82%
2022:11	-21.45%	25.39%
1998:02	-21.05%	25.87%
1998:10	-18.42%	27.58%
2009:04	-18.17%	11.74%
1999:04	-16.98%	23.28%
2000:07	-14.45%	1.94%
2015:07	-12.84%	-8.21%
2012:02	-12.42%	7.95%
1997:09	-11.79%	-0.46%
2001:11	-10.6%	10.31%
1992:05	-10.6%	13.83%
1998:11	-10.12%	1.88%

Panel B: Singapore		
Year : Month	WML	$E(R_m - r_f)$
1998:10	-46.79%	25.51%
2009:05	-31.7%	27.66%
1998:02	-22.86%	21.49%
2009:04	-20.71%	17.55%
2003:05	-14.52%	10.84%
2008:12	-14.34%	8.25%
1998:09	-14.26%	13.94%
1998:11	-12.94%	9.64%
1999:04	-12,00%	27.56%
2001:12	-10.82%	6.77%
1991:02	-10.63%	16.09%
2000:04	-10.02%	-0.70%
2012:01	-9.07%	12.97%
2002:01	-9.02%	9.62%
2016:03	-9,00%	8.71%

Panel C: UK		
Year : Month	WML	$E(R_m - r_f)$
2009:04	-34.65%	15.34%
2020:11	-26.34%	15.92%
2000:03	-16.4%	4.54%
2000:04	-13.91%	-6.04%
2009:03	-13.42%	3.64%
2001:11	-12.21%	2.11%
2000:05	-11.97%	-4.5%
2012:01	-11.74%	5.11%
2003:04	-11.37%	10.81%
2000:11	-10.09%	-7.33%
2009:08	-9.92%	6.34%
2002:11	-9.12%	3.02%
1999:04	-8.99%	5,00%
2001:10	-8.25%	2.27%
2023:01	-7.92%	6.64%

Panel D: Australia		
Year : Month	WML	$E(R_m - r_f)$
2000:04	-17.19%	-5.29%
2009:04	-15.01%	12.11%
2020:11	-13.38%	15. 05%
2009:03	-11.03%	17.18%
2009:05	-10.38%	11.35%
2022:07	-10.04%	7.77%
1999:04	-9.15%	8.22%
2009:07	-8.26%	10.44%
2000:05	-7.78%	-3.62%
2008:07	-7.46%	-7.37%
1988:01	-7.41%	-6.34%
2003:07	-6.43%	0.09%
2013:07	-6.13%	3.49%
1998:01	-5.91%	5.46%
2007:08	-5.80%	-4.47%

4.2 Optionality Regression

The methodology for the unconditional market model to the WML portfolio uses, in the regressions, the returns of the WML in month *t* as the dependent variable; the independent variables are the following ones (see next page):

- $\tilde{R}_{m,t}$: Excess market returns of each country at time *t*;
- $I_{B,t-1}$: Ex-ante bear market indicator, calculated using the cumulative excess market returns in the past 24 months. If the value is negative, the ex-ante bear market is one (1), otherwise it is zero (0);
- $\tilde{I}_{U,t}$: Up-market indicator variable, that is one (1) if the excess market returns are greater than the risk-free rate in a month and is zero (0) otherwise.

I ran the four regressions for each of the 24 countries and grouped them by individualism level, presenting the results using with the average of each individualism level (High, Medium, and Low). The results of these regressions are shown in Table 3. All the following regressions (1,2,3 and 4), so the entire methodology to study the unconditional market model to the WML portfolio was the same used by Daniel, and Moskowitz (2016).

$$\tilde{R}_{WML,t} = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\epsilon}_t \tag{1}$$

Regression 1, presented above, examines the relationship between the excess market returns ($\tilde{R}_{m,t}$) and the returns of the WML portfolio ($\tilde{R}_{WML,t}$) and studies the unconditional market model for the WML portfolio.

The results of regression 1 are shown in Table 3, Panel A. The estimated market beta ($\hat{\beta}_0$) is negative for all levels of individualism, and the results of the intercept ($\hat{\alpha}_0$) is higher for higher levels of individualism than for lower levels of individualism, being statistically significant at all levels. The intercept is statistically more significant as the level of individualism increases.

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + \beta_B I_{B,t-1})\tilde{R}_{m,t} + \tilde{\epsilon}_t \tag{2}$$

Regression 2, presented above, fits the conditional CAPM with the bear market indicator ($I_{B,t-1}$), consisting of the bear market indicator variable, excess market return $(\tilde{R}_{m,t})$, and the interaction between the bear market indicator and excess market return. The results of regression 2 are shown in Table 3, Panel B. This regression aims to capture the differences in expected returns and market beta during bear markets. When the market is down, the estimated excess market returns ($\hat{\beta}_0$) is a negative value for all levels of individualism, and the respective t-stat is also negative for all the levels of individualism. The estimated WML alpha ($\hat{\alpha}_0$) is positive and statistically significant at all the levels of individualism (High, Medium and Low). The estimated bear market indicator ($\hat{\alpha}_B$) and the estimated excess market returns ($\hat{\beta}_0$) are also both negative and not statistically significant for all the levels of individualism. Regarding the interaction between the bear market and the excess market returns the $\hat{\beta}_U$ is negative and statistically significant for all the levels of individualism.

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + I_{B,t-1}(\beta_U + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t \quad (3)$$

Regression 3, presented above, fits a new variable to understand whether the betas of the WML portfolio differ when we are up-market or down-market. For this purpose, I added the variable up-market indicator $(\tilde{I}_{U,t})$. The coefficient that shows the interaction between the excess market returns $(\tilde{R}_{m,t})$, the bear market indicator $(I_{B,t-1})$, and the up-market indicator $(\tilde{I}_{U,t})$ is the optionality coefficient $(\hat{\beta}_{B,U})$. This optionality coefficient $(\hat{\beta}_{B,U})$ is the value that captures the optionality effect and concludes that the momentum portfolio behaves like a short-call option on the market during the midst/end of the bear market (momentum crashes).

Daniel and Moskowitz (2016) captured the effect of the optionality coefficient for the US market. Looking into the results of regression 3, the values of the optionality coefficient for the entire sample of the 24 countries are like those obtained by Daniel, and Moskowitz (2016) for the USA market, and the results of the entire sample are homogeneous for all levels of individualism. The results of the optionality coefficient for the entire sample do not have any relationship with the level of individualism of each country. All the optionality coefficients $(\hat{\beta}_{B,U})$ are negative and statistically significant, whatever the level of individualism (either High, Medium, or Low). These results indicate that the WML portfolio has underperformed, dropping considerably even after rebounding from a bear market. When we are in a bear market, and the market return is negative, the estimates of the WML beta $\left(= \hat{\beta}_0 + \hat{\beta}_B\right)$ are always negative despite the level of individualism. When the excess market return is positive, i.e., there is a market recovery after a bear market, the value of the WML beta $\left(= \hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U}\right)$ is even more negative, which confirms the fact that the momentum is like a short call option on the market.

$$\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_U + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t \quad (4)$$

Regression 4, presented above, removes the effect of the bear market indicator, and maintains all the other variables. Looking into the results on Table 3, Panel D, the optionality coefficient still maintains the effect of a short-call option on the market, but with less strength, since the optionality coefficient ($\hat{\beta}_{B,U}$) increases in value and remains negative for all levels of individualism, i.e., is less negative for all levels of individualism.

Table 3. Market timing and optionality coefficient.

This table shows the estimated results of four monthly regressions for each of the three levels of individualism (High, Medium, and Low). The results shown are the average of the individual country results for each level, i.e., I ran the four regressions for all 24 countries in the sample and then aggregated and averaged each parameter according to its level of individualism. I have presented the results with the average for each level of individualism to make the results easier to read. Most of the regressions, except for a few countries mentioned in section 3, are between 1988:01 and 2023:06. In all cases, the dependent variable is the return on the WML portfolio, $R_{WML,t}$. The independent variables are the constant α_0, bear market indicator $I_{B,t-1,}$ which is equal to one when the cumulative excess market returns in the past 2 years if the value is negative and otherwise is zero; excess market returns $R^e_{m,t}$, and the up-market indicator which is equal to one if $R^e_{m,t} > 0$. The coefficient $\hat{\alpha}_0$ and $\hat{\alpha}_B$ are both multiplied by 100. The regression presented in Panel A is regression 1, in Panel B regression 2, in Panel C regression 3 and in Panel D regression 4.

The complete regression used in this table is the following:

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + I_{B,t-1}(\beta_U + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t \quad (3)$$

Index	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_B$	$\hat{\beta}_0$	$\hat{\beta}_{B,U}$	R^2_{adj}
Individualism		$\tilde{R}^e_{m,t}$	$I_{B,t-1}$	$I_{B,t-1} \cdot \tilde{R}^e_{m,t}$	$I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}^e_{m,t}$	
Panel A: Reg. 1						
Low	0.701		-0.222			0.082
	(2.68)		(-5.97)			
Medium	1.109		-0.269			0.092
	(4.33)		(-6.42)			
High	1.101		-0.246			0.083
	(5.04)		(-6.03)			
Panel B: Reg. 2						
Low	0.689	-0.428	-0.009	-0.471		0.177
	(2.25)	(-0.83)	(-0.19)	(-6.63)		
Medium	0.942	0.078	-0.090	-0.473		0.158
	(3.22)	(0.15)	(-1.52)	(-5.75)		
High	1.071	-0.394	-0.097	-0.396		0.130
	(4.31)	(-0.70)	(-1.82)	(-4.78)		
Panel C: Reg. 3						
Low	0.689	1.510	-0.009	-0.157	-0.649	0.213
	(2.32)	(2.17)	(-0.19)	(-1.50)	(-4.22)	
Medium	0.942	1.904	-0.090	-0.199	-0.631	0.176
	(3.25)	(2.24)	(-1.54)	(-1.66)	(-2.98)	
High	1.071	1.405	-0.097	-0.111	-0.672	0.150
	(4.36)	(1.83)	(-1.85)	(-1.01)	(-3.17)	
Panel D: Reg. 4						
Low	0.957		-0.018	-0.267	-0.408	0.205
	(3.54)		(-0.38)	(-2.87)	(-3.66)	
Medium	1.175		-0.099	-0.344	-0.287	0.166
	(4.27)		(-1.72)	(-3.31)	(-1.94)	
High	1.226		-0.104	-0.226	-0.397	0.144
	(5.26)		(-1.99)	(-2.27)	(-2.69)	

4.2.1 Index individualism vs Optionality Coefficient

To explore the evidence of any relationship between the optionality coefficient and their level of individualism, I plotted Fig 2. with each country's individualism value and its respective optionality coefficient ($\hat{\beta}_{B,U}$). I plotted a linear regression with this data on the graph, and it is possible to see a clear relationship between a country's level of individualism and its optionality coefficient, which means that the momentum portfolio performance is like a short call option in any market. The results of the regression of the relationship between index individualism and the optionality coefficient are shown in Appendix A, and it is again possible to see that there is no clear relationship between these two variables, although there is a slight negative trend between them. The estimated coefficient for the level of individualism is negative ($\hat{\beta}_I = -0.001$ and $\mathrm{t-stat} = -0.41$), and there is no apparent correlation between the variables since the estimated beta is quite close to zero and is not statistically significant.

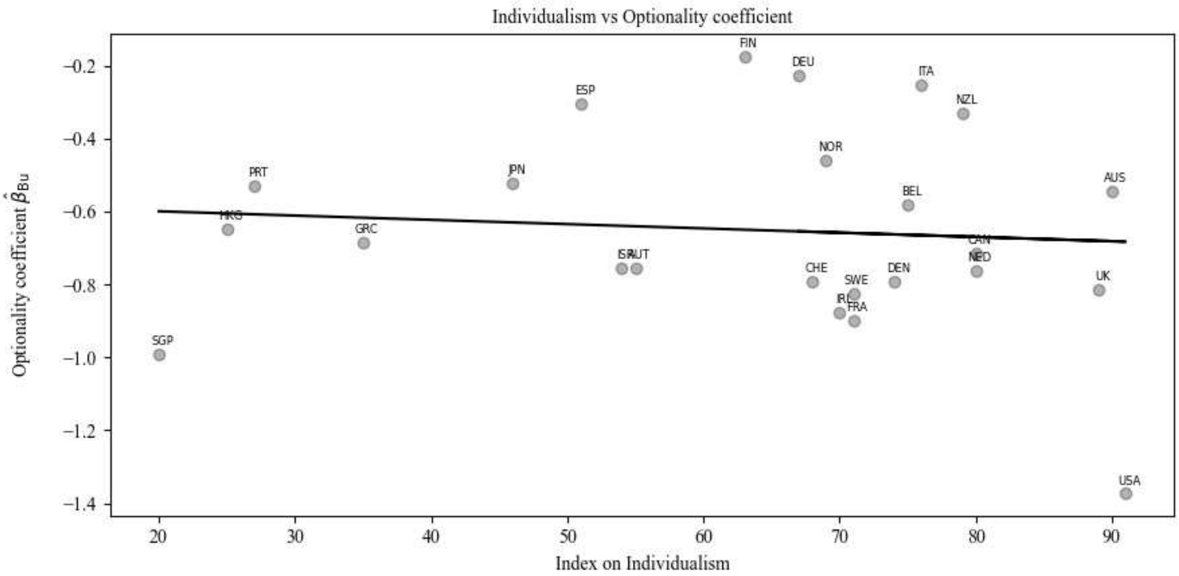

Figure 2. Relation between Index Individualism and Optionality Coefficient.
This figure presents the interaction between the level of individualism in each country and the respective optionality coefficient with all 24 countries in the sample. The optionality coefficient is the value that corresponds to the $\hat{\beta}_{B,U}$ coefficient from Table 3 Panel C.

4.2.2 Index individualism vs Optionality Coefficient without USA

Based on the results presented in the previous section (4.2.1), the USA is the country with the lowest optionality coefficient ($\hat{\beta}_{B,U} = -1.373$) and a significantly lower value than the rest of the sample (average the sample without USA $\hat{\beta}_{B,U} = -0.651$). Therefore, using the same methodology as in the previous section, I made a graph and a regression to understand the interaction between these two variables, but without data from the USA. Removing the USA from the sample is pertinent because, as they have such different optionality coefficients to the rest of the sample, it may be negatively influencing the results. Analyzing the results obtained without the USA Fig 3. and Appendix A, it is possible to observe that the relationship between the two variables is not very clear, but it changes from a relationship with a negative pattern to a positive pattern.

The value of the coefficient of the level of individualism went up from $\hat{\beta}_I = -0.001$ to $\hat{\beta}_I = 0.001$, but the increase is not significant enough to conclude that there is a positive relationship, but it is possible to conclude that in the cross-section of countries I chose, the coefficient of optionality of the USA has a more negative value than the rest of the sample, thus pulling the regression results down. In the sample without the USA, it is possible to conclude that when the value of the level of individualism increases, the value of the optionality coefficient decreases. One possible explanation for this result is that, according to Chui, Titman, and Wei (2010), when the level of individualism increases, the better the momentum returns.

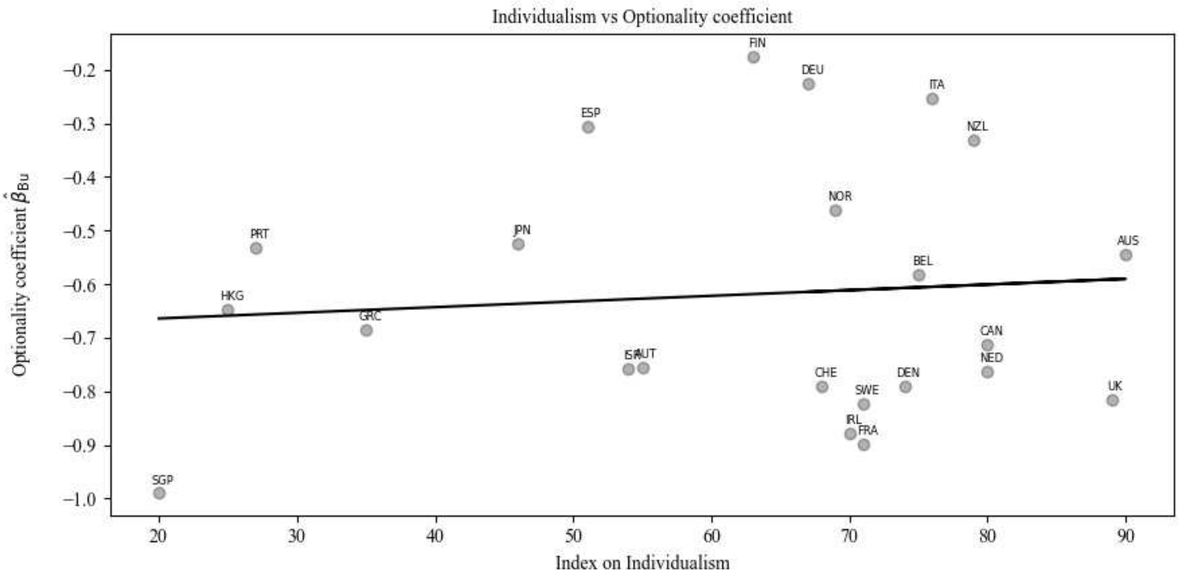

Figure 3. Relation between Index Individualism and Optionality Coefficient without USA.
This figure presents the interaction between the level of individualism in each country and the respective optionality coefficient without the USA data. The optionality coefficient is the value that corresponds to the $\hat{\beta}_{B,U}$ coefficient from Table 3 Panel C.

4.2.3 Optionality Coefficient vs Momentum Returns

Chui, Titman, and Wei (2010), studied the relationship between the level of individualism and momentum excess returns, proposing that there is a positive relationship between these two variables. So, to understand how momentum returns are affected by the optionality coefficient, I ran a regression with these two variables for each country. For a more detailed analysis, I have drawn Fig 4., which shows the point of intersection for each country according to its optionality coefficient and momentum returns. In the same Fig 4. I ran a linear regression to understand the relationship between the level of individualism and momentum returns and it is possible to see a positive ($\hat{\beta}_{B,U} = 0.003$ and $t - stat = 1.16$) pattern in the increase of momentum excess returns when the value of the optionality coefficient drops. I made the same analysis as I did in section 4.2.2, where I removed the data from the USA, but the results were not relevant. Although, they are presented both in a table with the regression values and in figure format in Appendix B, also the results of the linear regression (with all the sample – 24 countries) are shown in Appendix B.

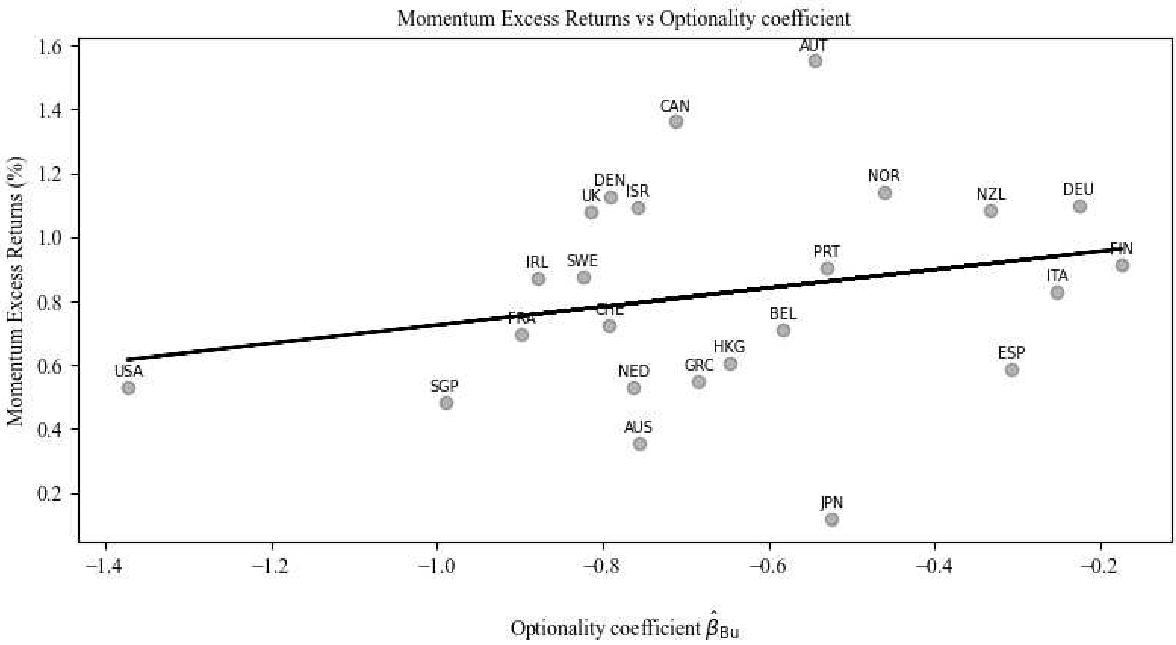

Figure 4. Relation between Optionality Coefficient and Momentum Excess Returns.

This figure presents the interaction between the optionality coefficient in each country and the respective momentum returns, with all 24 countries in the sample. The optionality coefficient is the value that corresponds to the $\hat{\beta}_{B,U}$ coefficient from Table 3 Panel C.

4.3 Momentum returns and estimated market variance

Daniel, and Moskowitz (2016) suggested that this optionality coefficient comes from the past loser's portfolio, i.e. when the market rebounds after the midst/end of the bear markets the momentum returns start to fall and the past losers behave like a short call on the market and the value of this option is not reflected in the prices of these assets. Therefore, the expected returns on the WML portfolio will be low, since the returns on the losers in a midst/end of the bear market are higher than expected, and according to the momentum portfolio, we sell the past losers (short) and buy (long) the past winners. When the variance increases the market value of an option also increases and it becomes less in-the-money, consequently more positively skewed. It is possible to notice that the expected return of the WML portfolio should be a decreasing function of the future market variance.

To analyze the effect of future market variance on the expected return of the WML portfolio in more depth, I ran the following regression:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_B . I_{B,t-1} + \gamma_{\sigma_m^2} . \hat{\sigma}_{m,t-1}^2 + \gamma_{int} . I_{B,t-1} . \hat{\sigma}_{m,t-1}^2 + \tilde{\epsilon}_t \quad (5)$$

Regression 5 comes from the methodology used by Daniel, and Moskowitz (2016) to study the moments of markets stress and the returns of the WML portfolio. Regression 5 has some similarities with the variables used in Table 3. The methodology used to divide the countries into three groups is the same as in Table 3., i.e., a division into three groups depending on the level of individualism of the country (High, Medium, and Low). Regarding the dependent variable in all the regression is the returns of the WML portfolio at month t, and the independent variables are the following:

- $I_{B,t-1}$: The ex-ante bear market indicator, a crucial variable, is calculated by the cumulative excess market returns in the past 24 months. If the value is negative, the ex-ante bear market is one, otherwise it is zero. This variable plays a significant role in our analysis;
- $\hat{\sigma}_{m,t-1}^2$: The daily variance of market returns for each country, computed from a rolling window of the last 126 days, and keeps only the last value of each month.

The regression reported in Panel A of Table 4 estimates the effect of the bear market indicator in estimating the future returns of the WML portfolio and shows a more slightly negative effect for countries with a lower level of individualism $\hat{\beta}_B = -0.208$ than compared to the other levels of individualism, although is not statistically significant t-stat = -0.399.

The regression reported in Panel B Table 4 studies the impact of market variance on the returns of the WML portfolio. The regression reported in Panel C Table 4 reports the effect of the two independent variables simultaneously on WML portfolio returns. The regression reported in Panel D Table 4 shows the result of the interaction between the bear market and the market variance, and the regression reported in Panel E Table 4 reported the analyses of the effect for all the independent variables combined. Analyzing the results of Panel C, Table 4, the coefficients of the bear market and the variance, in this context of the international sample, the variance negatively predicts the returns of the momentum strategy, and the bear markets impact positively. Regarding the relation of the market volatility and the momentum returns Kevin, Wang, and Jianguo (2015) studied the impact of market volatility on the momentum strategy, also finding that market volatility could predict the returns of the momentum. The momentum returns are predictable and occur during bull markets following periods of low volatility, according to the findings of Barroso and Wang (2021).

Insights from Panels D and E of Table 4 simplify our understanding of momentum returns. It becomes clear that these returns tend to deteriorate slightly during periods of bear markets and high market variance. This effect is more pronounced in countries with a higher level of individualism, which is consistent with work of Daniel, and Moskowitz (2016).

Chui, Titman, and Wei (2010) suggested that volatility is positively related to individualism and negatively correlated with the momentum profits. The results of the regressions reported in Panel D and E of Table 4 have a difference in the point estimate, however it is not statistically significant that countries with a higher level of individualism have the impact of the interaction between market variance and the bear market more negative.

Table 4. Estimated bear market with market variance and momentum returns.

This table presents the regression coefficients and respective t-statistics showing that the excepted variance of the market and the bear market indicator independently forecast future momentum returns. The base regression in this table is the following:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_B . I_{B,t-1} + \gamma_{\sigma_m^2} . \hat{\sigma}_{m,t-1}^2 + \gamma_{int} . I_{B,t-1} . \hat{\sigma}_{m,t-1}^2 + \tilde{\epsilon}_t \quad (5)$$

The dependent variable is always the same in all the regressions in the table, the monthly momentum returns $\tilde{R}_{WML,t}$. The independent variables are the bear market indicator $I_{B,t-1}$, the daily variance of the market calculated based on the last 126 days and prior to month t $\hat{\sigma}_{m,t-1}^2$. All regressions use monthly data from 1988:01 to 2023:06 with the exceptions of some countries mentioned in section 3. The coefficients $\hat{\gamma}_0$ e $\hat{\gamma}_B$ are both multiplied by 100. Panel A and Panel B report the results of the bear market indicator and the expected variance of the market individually. Panel C presents the results of the bear market indicator and the expected variance of the market together, while Panel D presents the results of the interaction between the bear market indicator and the expected variance of the market. The last Panel (E) shows the variables' results together. All the panels are divided into three groups (High, Medium, and Low) depending on the country's level of individualism.

Index on Individualism	$\hat{\gamma}_0$	$\hat{\gamma}_0$	$\hat{\gamma}_{\sigma_m^2}$	$\hat{\gamma}_{int}$
Panel A: Reg. 1				
Low	0.663	-0.250		
	(2.02)	(-0.46)		
Medium	0.817	0.434		
	(2.61)	(0.64)		
High	0.957	-0.073		
	(3.60)	(-0.05)		
Panel B: Reg. 2				
Low	1.106		-0.026	
	(2.92)		(-2.16)	
Medium	1.213		-0.011	
	(3.29)		(-1.01)	
High	1.452		-0.026	
	(4.81)		(-2.46)	
Panel C: Reg. 3				
Low	1.106	0,132	-0,028	
	(2.82)	(0.25)	(-2.16)	
Medium	1.142	0,790	-0.018	
	(3.10)	(1.14)	(-1.37)	
High	1,410	0.635	-0.037	
	(4.62)	(1.09)	(-2.70)	
Panel D: Reg.4				
Low	0.740			-0,018
	(2.47)			(-1.55)
Medium	0.969			-0,001
	(3.46)			(-0.25)
High	1.110			-0.020
	(4.59)			(-1.81)
Panel E: Reg.5				
Low	1.299	-0.248	-0.038	0.014
	(2.33)	(-0.19)	(-1.42)	(0.46)
Medium	1.202	0,588	-0,020	0.005
	(2.42)	(0.64)	(-0.93)	(0.23)
High	1.362	0.709	-0.032	-0.004
	(3.23)	(0.83)	(-1.14)	(-0.20)

4.4 Dynamic weighting of the momentum portfolio

According to Barroso, and Santa-Clara (2015) and Daniel, and Moskowitz (2016), momentum crashes can be avoided, and the performance of the WML portfolio can be improved if the weights of the WML portfolio are dynamically adjusted using the predicted returns and the variance of the strategy. Given that the previous sections have shown that variance in bear market periods is a factor that affects the returns of the dynamic portfolio, a dynamic portfolio was constructed for each of the countries to minimize these negative impacts of variance on the returns of the dynamic portfolio. To create the dynamic portfolio with the objective of having an adjusted WML portfolio, it was necessary to use the Optimal Weights formula, where the weights are adjusted upwards or downwards to create a constant volatility strategy proposed by Barroso and Santa-Clara (2015). This dynamic portfolio adjusts the weights for each return based on the forecasted returns of the WML strategy and the variance of the strategy. I used the knowledge from the previous sections to create this dynamic portfolio.

4.4.1 Optimal Weights

To come up with the optimal value for portfolio weights, I used the same formula that Daniel, and Moskowitz (2016) used, which aims to maximize the unconditional Sharpe ratio in the sample, thus being the optimal weighting on the risky asset (WML) at time *t-1*:

$$w_{t-1}^{*} = \left(\frac{1}{2\lambda}\right)\frac{\mu_{t-1}}{\sigma_{t-1}^{2}} \tag{6}$$

The variables used to calculate the optimal weights are:

- $\mu_{t-1} = E_{t-1}\left[R_{WML,t}\right]$, which is the expected return calculated for the WML portfolio over the coming month. The calculation of this expected return comes from the same regression of Panel D section 4.3. The regression used is the following:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int}.I_{B,t-1}.\hat{\sigma}_{m,t-1}^{2} + \tilde{\epsilon}_t \tag{7}$$

- $\sigma_{t-1}^{2} = \mathrm{E}_{t-1}\left[\left(\left(\mathrm{R}_{\mathrm{WML,t}}^{2} - \mu_{t-1}\right)\right)^{2}\right]$, which is the conditional variance of the return of the WML portfolio over the coming month (22 days). This variable is computed using the following steps: first, the GJR-GARCH estimate of future 22-day returns volatility is computed (details on this model can be found in section 4.4.2). Second, the volatility of the lagged 126-day returns of the WML portfolio are computed. Then, the volatility of the future realized returns of the 22-day WML portfolio ($\hat{\sigma}_{22,t+1}$) is regressed on: the GJR-GARCH estimate ($\hat{\sigma}_{GARCH,t}$), the volatility of the lagged 126-day returns of the WML portfolio ($\hat{\sigma}_{126,t}$) and a constant, according the formula:

$$\hat{\sigma}_{22,t+1} = \alpha + \beta_0 \hat{\sigma}_{GARCH,t} + \beta_V \hat{\sigma}_{126,t} \tag{8}$$

This adjusted estimate of future realized volatility is then one of the inputs to the dynamic weighting of the WML portfolio. Since the result of the regression was the volatility and, to compute the dynamic weights, I needed the variance, I squared the value obtained.

The last component (λ) is a time-invariant scalar that controls the return and risk of the dynamic portfolio. This scalar was computed so that the in-sample volatility of the dynamic weighted portfolio matched the market volatility during the same period. Each country has a different value of λ. So, to calculate this variable, I used the same methodology as Barroso, and Santa-Clara (2015), on their strategy of constant volatility, finding the value of λ by dividing the variance of the market by the variance of the dynamic-weighted non-adjusted momentum portfolio (DNAMP), i.e., the dynamic-weighted portfolio constructed using a weight formula that omits λ.

$$\lambda = \frac{\sigma^2_{Market}}{\sigma^2_{DNAMP}} \tag{9}$$

4.4.2 The GJR-GARGH Model

To forecast the volatility of the WML portfolio, I regressed an adjusted model of the GARCH model GJR-GARCH Model proposed by Glosten, Jagannathan, and Runkle (1993) to the series of returns of the WML portfolio. The process of GJR-GARCH is defined by the following formula:

$$R_{WML,t} = \mu + \epsilon_t \tag{10}$$

The $\epsilon_t \sim \mathcal{N}(0, \sigma_t^2)$ and the variation of σ_t^2 is controlled by the process:

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \big(\alpha + \gamma I(\epsilon_{t-1} < 0)\big)\epsilon_{t-1}^2 \tag{11}$$

The variable I used to monitor the evolution of variance was:

- $I(\epsilon_{t-1} < 0)$, that is the binary indicator variable and is equal to one (1) when $\epsilon_{t-1} < 0$, and it is zero (0) otherwise.

I used maximum likelihood to estimate the parameters $(\mu, \omega, \alpha, \gamma, \beta)$, using the data from the entire time series.

Re-stating the methodology described on section 4.4.1, following the same approach of Daniel, and Moskowitz (2016), with the results of the GJR-GARCH model and the rolling window of the last 126 days of the volatility WML returns volatility, I regress the future realized 22-day WML return volatility ($\hat{\sigma}_{22,t+1}$) on them. The regression of the future realized 22-day WML return volatility has the goal estimating the β exposure of $\hat{\sigma}_{22,t+1}$ to the GARCH estimate and the historical 126-days WML volatility, thus containing hindsight, and the process is defined by the following formula 8 shown before in section 4.4.1:

$$\hat{\sigma}_{22,t+1} = \alpha + \beta_0 \hat{\sigma}_{GARCH,t} + \beta_V \hat{\sigma}_{126,t} \tag{8}$$

The regression is based on the GJR-GARCH values $\hat{\sigma}_{GARCH,t}$ and the rolling window of the last 126 days returns of the WML portfolio $\hat{\sigma}_{126,t}$ of each country, so I created 24 regressions. The results of the ordinary least squares of the coefficients and following t-statistics are shown in Table 5. Having the β outputs available, each month I compute the fitted estimated of the volatility of WML returns over the next month ($\hat{\sigma}_{22,t+1}$) using the linear combination described in equation (12), that is subsequently used as the input of the dynamic momentum portfolio weight (section 4.5).

Table 5. Future realized 22-day WML return volatility

This table shown the ordinary least squares of the coefficients and following t-statistics of the regression 12 of each country. The table continues the next page.

Country	$\hat{\alpha}$	$\hat{\beta}_0$	$\hat{\beta}_V$	R^2_{adj}
United States (USA)	0.017	0.626	0.189	0.575
	(15.58)	(54.62)	(15.52)	
Australia	0.024	0.530	0.193	0.337
	(18.98)	(38.26)	(13.16)	
United Kingdom (UK)	0.018	0.637	0.136	0.538
	(17.55)	(54.25)	(10.79)	

Country	$\hat{\alpha}$	$\hat{\beta}_0$	$\hat{\beta}_V$	R^2_{adj}
Canada	0.024	0.499	0.275	0.467
	(17.59)	(40.26)	(20.14)	
Netherlands	0.021	0.750	0.076	0.582
	(14.90)	(57.18)	(5.51)	
New Zealand	0.019	0.568	0.251	0.468
	(14.01)	(24.01)	(12.11)	
Italy	0.019	0.604	0.210	0.494
	(14.58)	(48.33)	(15.57)	
Belgium	0.014	0.686	0.176	0.538
	(10.66)	(48.93)	(12.66)	
Denmark	0.034	0.376	0.358	0.300
	(18.26)	(25.55)	(23.47)	
France	0.015	0.685	0.134	0.549
	(14.04)	(58.95)	(11.04)	
Sweden	0.013	0.766	0.108	0.598
	(10.30)	(50.33)	(7.18)	
Ireland	0.073	0.403	0.293	0.331
	(19.43)	(34.02)	(23.13)	
Norway	0.036	0.625	0.151	0.417
	(16.65)	(45.27)	(10.35)	
Switzerland	0.011	0.683	0.181	0.548
	(9.77)	(54.47)	(14.10)	
Germany	0.022	0.589	0.182	0.487
	(17.63)	(49.25)	(14.56)	
Finland	0.014	0.624	0.266	0.529
	(7.91)	(31.49)	(14.27)	
Austria	0.024	0.536	0.276	0.476
	(14.86)	(37.96)	(19.41)	
Israel	0.011	0.911	-0.039	0.458
	(6.84)	(45.11)	(-2.11)	
Spain	0.027	0.551	0.206	0.424
	(18.25)	(44.63)	(15.26)	
Japan	0.027	0.495	0.191	0.385
	(21.78)	(48.79)	(15.58)	
Greece	0.047	0.402	0.315	0.389
	(19.79)	(29.89)	(21.21)	
Portugal	0.068	0.415	0.166	0.236
	(30.61)	(30.46)	(13.86)	
Hong Kong	0.021	0.750	0.076	0.582
	(14.90)	(57.18)	(5.51)	
Singapore	0.024	0.587	0.168	0.450
	(17.97)	(55.50)	(14.46)	

4.5 Dynamic strategy of Momentum

To construct the dynamic portfolio, I applied the insights from the previous sections, where I first obtained the monthly dynamic weights that I computed for each country. With the dynamic weights computed for each country, I multiplied them by the monthly WML portfolio returns.

$R_{D,t}$: Returns of the dynamic portfolio month t;

w_{t-1} : Dynamic weights month t-1;

$R_{WML,t}$: Return of the WML portfolio month t

I used the following methodology:

$$R_{D,t} = w_{t-1} * R_{WML,t} \tag{13}$$

Having the dynamic portfolio for all the countries, for a more detailed analysis of the results obtained, I plotted Fig.5, which shows the average of the dynamic weights for each level of individualism (High, Medium, Low). I also plotted a constant line with a value of one which represents a static WML portfolio with weights equal to one.

After analyzing the obtained graphs (see Fig. 5 in the following page), I reached the conclusion that there is no apparent correlation between the level of individualism and the calculation of dynamic weights. This is because momentum crashes occur at approximately the same time in all the countries in the sample I used, so the weights are adjusted at similar times, and the absolute value of the weights is also similar. The momentum excess returns are higher for countries with higher level of individualism, which justifies the differences in dynamic weights among the three levels of individualism. This implies that the intensity of momentum crashes is almost the same regardless of the country's level of individualism.

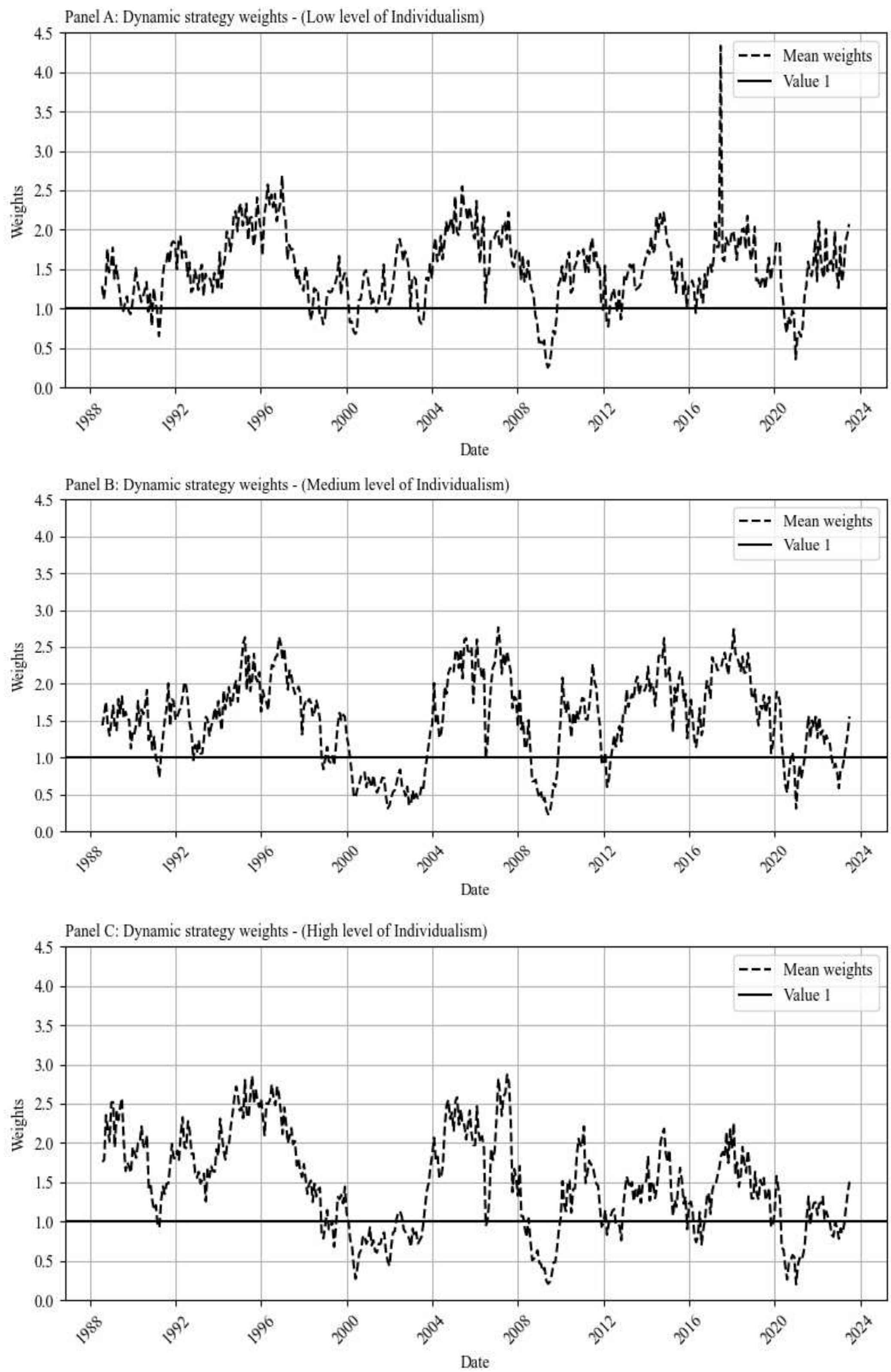

Figure 5. Dynamic strategy weights are divided by the level of individualism.

The three charts present the average of the optimal weights calculated in section 4.4.1 for each country, grouped according to their level of individualism (High, Medium, and Low). I applied a constant weight strategy to all the charts to compare the weight initially allocated in the momentum strategy to the optimal weight allocated in the dynamic strategy for the momentum strategy.

4.5.1 New portfolio of Momentum

To create a new investment strategy with the insights I gained in the previous sections, I created a new High-minus-Low portfolio, i.e. the portfolio whose returns are computed as the average returns of countries with a high level of individualism deducted by the average returns of the countries with a low level of individualism. The reason behind the creation of this new portfolio was the fact that countries with a higher level of individualism have better returns than countries with a lower level of individualism. So, I built a new portfolio with monthly returns based on the dynamic WML portfolio and I also made a new High-minus-Low portfolio for the initial WML portfolio without the adjusted weights to compare the evolution of the strategy's returns with and without the adjusted weights.

The new portfolio's statistical results, detailed in Table 6, provide a comprehensive overview of its performance. These results offer valuable insights into the portfolio's returns, volatility, Sharpe ratio, and realized skewness.

For countries with higher level of individualism average returns of the dynamic and momentum portfolios also increase. This increase is particularly noticeable when moving from a low to medium level of individualism. Interestingly, volatility in both portfolios' peaks at the medium level of individualism, with no discernible pattern at the extreme levels. The Sharpe ratio, a risk-adjusted performance measure, also increases with returns. Daniel, and Moskowitz (2016) suggesting that the dynamic strategy doubles the Sharpe ratio, and this pattern is possible to observe in all the new investments portfolios (High-minus-Low). According to what Harvey and Siddique (2001) proposed, momentum returns are associated with skewness.

However, for the cross-section of countries used in the isolated High, Medium, and Low portfolios, this pattern is not clear, not for the dynamic portfolios or for the initial momentum portfolios. This pattern is only evident in the two new High-minus-Low portfolios, where increasing returns correspond with decreasing skewness.

Notably, the dynamic High-minus-Low portfolio exhibits lower skewness and higher returns, unlike the new High-minus-Low initial momentum portfolio.

Table 6. Return Statistics of the new portfolio

This table presents the characteristics of the monthly returns of the new High-minus-Low momentum portfolios of both the dynamic and the initial momentum portfolios over the entire sample from 1988:01 to 2023:07, except for a few countries mentioned in section 3. The statistical characteristics of the returns are presented through the averages of the countries grouped according to their level of individualism. Average returns and volatility are presented in percentages and annualized. SR is the annualized Sharpe ratio. Max is the maximum value of the returns, and Min is the minimum value of the returns of the entire sample. SK Real. is the realized skewness calculated using the formula $\log(1 + r_{WML} + r_f)$.

Return Statistic	Dynamic Portfolio High	Dynamic Portfolio Medium	Dynamic Portfolio Low	Dynamic Portfolio High-minus-Low	Momentum Portfolio High	Momentum Portfolio Medium	Momentum Portfolio Low	Momentum Portfolio High-minus-Low
$\bar{r}$	24.2	23.1	16.4	6.9	12.3	12.1	7.3	4.7
σ	11.5	12.6	12.5	11.6	12.1	13.7	11.1	8.2
SR	1.9	1.7	1.2	0.6	1.0	0.8	0.6	0.6
SK Real.	-0.10	-0.08	-0.62	-0.24	-2.18	-1.42	-2.82	0.19
Max	11.3	15.6	16.9	13.1	10.9	14.4	9.0	10.3
Min	-9.0	-10.8	-16.9	-15.9	-24.9	-25.2	-25.0	-6.7

4.5.2 The new portfolio and optionality coefficient

In this section, I will be exploring the impact of the optionality coefficient on Momentum factor profits in new portfolios. Considering the optionality coefficient and its significant results for each of the 24 countries in the sample, I decided to study its effect in these two new portfolios I developed. The methodology I used was the same as in section 4.2 with some adaptations, since in this new High-minus-Low portfolio I used the average of the excess market returns of the countries with a high level of individualism and the countries with a low level of individualism. To obtain the bear market indicator variable and the up-market indicator, the methodology was the same as described in section 4.2 but using the average excess market return for each of the individualism levels. The key finding from Table 7 is that, unlike the previous results in section 4.2 where the optionality coefficient for each country is negative, for these new portfolios the value of the optionality coefficient is positive. These results thus show that for the cross-section of countries used, optionality (optionality coefficient) doesn't play any role in Momentum factor profits. Table 7 presents the results from the optionality coefficients for each High-minus-Low portfolio.

Table 7. Optionality coefficient in the new portfolio

This table presents the estimated monthly results for the two new High-minus-Low portfolios, the initial momentum portfolio, and the dynamic portfolio. The results presented except for a few countries mentioned in section 3 are between the period 1988:01 and 2023:06. The regression used in this table is the same as in section 4.2 regression 3. The dependent variable is the return on the WML portfolio, ($R_{WML,t}$). The independent variables are the constant (α_0), bear market indicator ($I_{B,t-1}$) which is equal to one when the cumulative excess market returns in the past 2 years if the value is negative and otherwise is zero; excess market returns ($R^e_{m,t}$) , and the up-market indicator which is equal to one if $R^e_{m,t} > 0$. The coefficient $\hat{\alpha}_0$ and $\hat{\alpha}_B$ are both multiplied by 100.

Portfolio High-minus-Low	$\hat{\alpha}_0$	$\hat{\alpha}_B$	$\hat{\beta}_0$	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	R^2_{adj}
	1	$I_{B,t-1}$	$\tilde{R}^e_{m,t}$	$I_{B,t-1} \cdot \tilde{R}^e_{m,t}$	$I_{B,t-1} \cdot I_{U,t} \cdot \tilde{R}^e_{m,t}$	
Momentum (WML) portfolio	0.430	0.620	-0.057	-0.479	0.796	0.006
	(2.75)	(-1.54)	(-0.93)	(-1.93)	(2.06)	
Dynamic portfolio	0.006	-0.008	-0.074	-0.234	0.698	-0.003
	(2.70)	(-1.47)	(-0.90)	(-0.70)	(1.32)	

5. Conclusion

This dissertation discusses the relationship between the level of individualism and momentum crashes, focusing on the optionality coefficient in a diverse sample of countries. The primary source for the analysis is the "Momentum Crashes" paper, so I tested several of the approaches used in this article. My sample comprises 24 countries over a period that ranges from 188:01 to 2023:06. For the universe of the sample, it is possible to conclude that momentum returns are affected by the level of individualism of the countries, but the level of individualism does not impact on momentum crashes, given that momentum crashes occur globally due to falls in the markets. The level of individualism is neither an enhancer nor a mitigator of these strategy crashes.

The optionality coefficient ($\hat{\beta}_{B,U}$) for the cross-section of countries that I selected, on an individual level for each, behaved in a similar way to the proposed by Daniel, and Moskowitz (2016): during a period when there is a bear market and contemporaneous market returns that are negative, the sum of $\left(= \hat{\beta}_0 + \hat{\beta}_B\right)$ then, in a period when contemporaneous market returns turn positive, the sum of $\left(= \hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U}\right)$ has a lower value compared to what would happen if contemporaneous market returns were negative. Therefore, this approach shows that market rebounds following bear market periods impact the momentum portfolio negatively, making the returns of the WML portfolio poor. This confirms that these momentum portfolios behave like a short call option on the market across the whole sample of countries.

Concerning how the countries level of individualism affects the optionality coefficient ($\hat{\beta}_{B,U}$) for the whole sample, the pattern was negative, so countries with higher level of individualism tend to have lower value of optionality coefficient. However, the relationship is not robust enough, because excluding the USA data from the sample, makes the results significantly different, as the relationship reverses (it becomes positive): so, countries with a higher level of individualism are positively associated with higher optionality coefficient values ($\hat{\beta}_{B,U}$). The possible explanation for this inverse pattern when removing the USA data from the sample is that the value of the USA optionality coefficient is significantly lower than that of the other countries.

Variance is another important factor in this study since when variance increases, the value of the call option increases, and variance predicts momentum returns negatively. To predict momentum returns in periods of low market and high variance, I created a linear combination of the variance indicator and low market, concluding that the interaction of these two variables negatively predicts momentum returns for any country's level of individualism, with no specific pattern for countries with a higher or lower level of individualism.

Looking at the dynamic portfolios created for the entire cross-section of countries to mitigate momentum crashes, the respective optimal weights assigned were not affected by the level of individualism of the country, which was to be expected since the pattern of momentum crashes does not vary according to the country's level of individualism. The pattern for momentum returns increase for countries with higher level of individualism is still there for dynamic portfolios.

The main conclusion of the dissertation is that the country's level of individualism and momentum crashes are not closely related, and during the market rebounds after the midst/end of the bear markets the country's level of individualism does not affect the behavior of the momentum strategy which remains with a short call option behavior in the market (optionality coefficient).

APPENDIX

Appendix A: Individualism vs Optionality Coefficient

Table 8. Results of the linear combination of the index on individualism vs. optionality coefficient

This table shows the results of the linear combination, coefficients, and respective t-statistics), which relates the level of individualism of the country and the optionality coefficient. The dependent variable is the optionality coefficient, and the independent variable is the level of individualism in each country.

Individualism vs Opc. Coefficient	$\hat{\alpha}_0$	$\hat{\beta}_I$	R^2_{adj}
Coef. est.	-57.622	-0.001	-0.038
T-stat	(-3.02)	(-0.41)	

Table 9. Results of the linear combination of the index on individualism vs. optionality coefficient without USA.

This table shows the results of the linear combination, coefficients, and respective t-statistics, which relates the level of individualism of the country and the optionality coefficient. The dependent variable is the optionality coefficient, and the independent variable is the level of individualism in each country.

Individualism vs Opc. Coefficient	$\hat{\alpha}_0$	$\hat{\beta}_I$	R^2_{adj}
Coef. est.	-68.518	0.001	-0.039
T-stat	(-4.13)	(0.42)	

Appendix B: Optionality Coefficient vs Momentum Excess Returns

Table 10. Results of the linear combination of the optionality coefficient vs. momentum excess returns

This table shows the results of the linear combination, coefficients, and respective t-statistics, which relates the level of individualism of the country and the optionality coefficient. The dependent variable is the momentum excess returns, and the independent variable is the optionality coefficient.

Individualism vs Opc. Coefficient	$\hat{\alpha}_0$	$\hat{\beta}_{B,U}$	R^2_{adj}
Coef. est.	1.015	0.003	0.015
T-stat	(5.79)	(1.16)	

Table 11. Results of the linear combination of the optionality coefficient vs. momentum excess returns without USA.

This table shows the results of the linear combination, coefficients, and respective t-statistics, which relates the level of individualism of the country and the optionality coefficient. The dependent variable is the momentum excess returns, and the independent variable is the optionality coefficient.

Individualism vs Opc. Coefficient	$\hat{\alpha}_0$	$\hat{\beta}_{B,U}$	R^2_{adj}
Coef. est.	0.986	0.002	-0.019
T-stat	(4.88)	(0.77)	

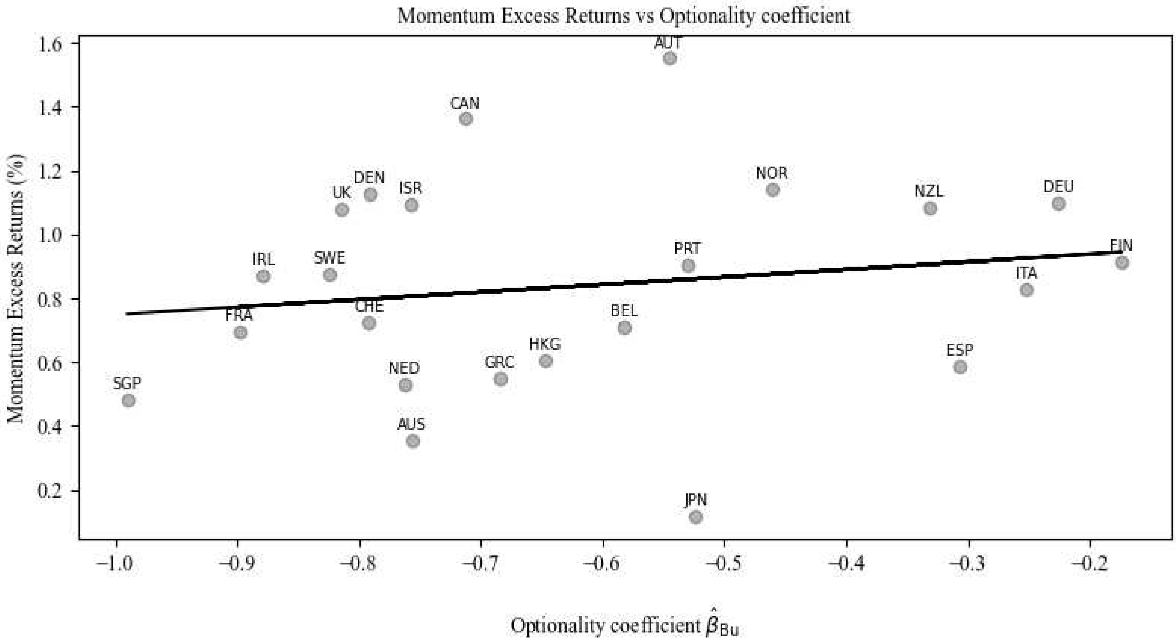

Figure 6. Relation between Optionality Coefficient and Momentum Excess Returns without USA.

This figure presents the interaction between the optionality coefficient in each country and the respective momentum excess returns, without the data of the USA. The optionality coefficient is the value that corresponds to the $\hat{\beta}_{B,U}$ coefficient from Table 3 Panel C.

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