Momentum pricing and trading, and economic uncertainty regimes

Jorge M. Uribe

Riskcenter and UB School of Economics, University of Barcelona, Barcelona, Spain.
Contact: juribegi9@alumnes.ub.edu

This version March 13 2017

Abstract

The effects of momentum on excess equity returns are not constant across different regimes of economic uncertainty. They tend to decrease in high uncertainty regimes for portfolios that do not depend significantly on prior returns, and to increase for portfolios that do depend, either negatively or positively. We used a smooth-transition regression framework that allows us to explore the evolving nature of momentum pricing in the context of two beta representations of the equity premium: Fama-French three and five-factor models. Here, economic uncertainty is incorporated as an economic regime that impacts the probability distribution of momentum. Our model considers two extreme states: one of *low* uncertainty and one of *high* uncertainty. We also calculate pricing errors of each model under the two regimes. We analyzed 25 value-weighted portfolios sorted according to momentum and size, 100 portfolios sorted according to size and book to market (B/M), and four univariate portfolios according to size, B/M, profitability and investment. In general, the models perform better during regimes of relatively high uncertainty, and those that incorporate momentum perform the best. Nevertheless, this superior performance comes at a cost. The abnormal returns produced by momentum *disappear* during high uncertainty regimes in the market, its Sharpe ratio goes to *zero,* the kurtosis of the momentum strategy *doubles,* and its skewness becomes *negative.* Our simple recommendation is not to trade momentum when you expect high economic uncertainty.

JEL: G12, G14, G02, D81.

Keywords: uncertainty, asset pricing, momentum, Fama-French, smooth-transition, conditional factor model.

1. Introduction

We study the relationship between economic uncertainty and momentum, considering the latter as a risk factor explaining the equity premia. We find that the effects of momentum on excess returns vary significantly across different uncertainty regimes. This is consistent with the view of uncertainty as an economic *state* rather than as a factor to be included in the set of regressors. We found that momentum loses relevance in regimes of high uncertainty for most of the portfolios analyzed. One important exception being those portfolios that are highly exposed to the momentum factor *even* under low uncertainty regimes. We also present evidence of the unstable nature of a momentum trading strategy (buying past winners and selling past losers of the previous 2-12 months), under the two regimes of uncertainty that we identified. From this, we would advise against momentum trading when uncertainty is high.

Momentum continues being a pervasive anomaly (Asness et al., 2013). After Jegadeesh and Titman (1993) found that previous winners in the stock market outperform previous losers, in a significant way, making it possible to attain Sharpe ratios that exceed that of the market itself, momentum trading has become an astonishing popular strategy among practitioners and of outstanding interest for academics. This popularity seems to have lost some of its initial impetus due to the even more astonishing higher order risks that momentum trading imposes on investors, such as an extremely fat-tailed and negatively-skewed distribution of gains (Daniel and Moskowitz, 2012). The initial strategy that basically consisted of buying past winners and selling past losers, has made room for more sophisticated ones that use time-varying hedging mechanisms seeking to reduce terrifying momentum crashes (Blitz et al., 2011; Daniel and Moskowitz, 2012; Barroso and Santa-Clara, 2015). Yet momentum trading remains in force today.

Therefore, when we turn our attention to asset pricing it is not surprising that momentum remains as a puzzle in the explanation of the equity premium. Countless factors have been proposed to analyze this premium and its related anomalies[1]. However, the ever-growing set of factors that has been explored so far still has not provided a reliable substitute for momentum at explaining excess returns. One popular model, recently proposed by Fama and French (2015) includes, on top of the traditional three factors: *market*, *size* and *book to market*; two factors related to *investment* strategies (conservative or aggressive), and firms' *profitability* (robust or weak). And even regarding this new version of their classical three-factor model, Fama and French (2016) acknowledge the importance of including momentum within the set of regressors. In short, they say that portfolios sorted according to winners and losers in the prior 2-12 months remain elusive to the explanation provided by the five-factor model, unless the momentum factor is included in the right-hand-side (RHS) variables' set alike.

On this playing field, it is quite natural that both, rational explanations (Johnson, 2002; Sagi and Seasholes, 2007; Liu et al., 2008) and other more behavioral in nature (Daniel et al., 1998; Hong and Stein, 1999; Cooper et al., 2004) have been tried seeking for a definite understanding of the momentum anomaly. Basically, the former models point out to some

---

[1] See for example the recent work by Campbell et al. (2016) who, as the authors say, used an excessively reduced subset of 313 factors in their analysis.

kind of market friction, heterogeneous information, firms' specific characteristics, or the growth rate of industrial production, to account for momentum; while the latter resort to biases in investors' perceptions to explain momentum profits. In this second strand, the general reasoning embraces overconfident (Daniel et al, 1998; Chui et al., 2010) or over-reacting (Hong and Stein, 1999) investors who generate the momentum puzzle as new wages of information arrive to the market[2].

In any case, there is not a completely satisfactory narrative about what drives momentum. There are even doubts about whether momentum is really *momentum* or instead if immediate past performance is actually a proxy for medium-horizon past performance (Novy-Marx, 2012). It seems that macroeconomic factors are unable to capture momentum profits after considering market microstructure concerns (Cooper et al., 2004), and that other sorts of explanations such as the famous disposition effect have been discarded as an explanation for momentum as well (Birru, 2015). Thus momentum remains as an elusive phenomenon.

As if the elusive nature of momentum were not enough, we also know that its relationship with excess returns and systemic risk factors is non-linear. That is, momentum has time-varying market betas (Grundy and Martin, 2001) and hedging using those varying betas in real time does not work. This is because the main source of predictability (and variability) of the risk implied by momentum strategies are not the betas, but the idiosyncratic conditional volatility, as documented by Barroso and Santa-Clara (2015). To put it briefly, momentum does not seem to share with other more theoretically grounded factors the comfortable linearity ubiquitous in traditional equivalences with stochastic discount factor representations of the market prices, $p = E(mx)$[3]. For this reason, its treatment requires to make room for time varying risk prices, as function of state variables[4].

In this study we fit to the data a conditional pricing model, but we only include momentum within the set of conditioned variables. That is, we condition the effect of momentum on excess returns, on a state variable that is a macroeconomic uncertainty indicator. In this way, we add to a nascent strand of the financial literature that analyzes the impact of uncertainty on stock prices (Brogaard and Detzel, 2015; Segal et al., 2015; Bali and Zhou, 2016; Chuliá et al., 2017a)[5]. Different from them, we do not treat uncertainty as a *risk factor* in the set of RHS variables used to explain the returns. It is our contention that

[2] See Barberis et al. (2015) and references there in for an example of extrapolative investors that have been used as well to generate momentum.

[3] See Cochrane (2005), Chapters 1-3.

[4] That is, for conditional pricing in which nonlinear effects arise in the form of additional terms that appear in the pricing equation. This is described for example by Jagannathan and Wang (1996); Lettau and Ludvigson (2001); Cochrane (2005), Chapter 8, and Maio and Santa-Clara (2012), footnote 3.

[5] In this branch of the literature the implicit assumption if that uncertainty proxies for systematic economic news, and investors are ultimately concerned about business cycle risks. Therefore, they require a premium for exposure to it. This approach finds support on a recent study by Boons (2016) who document consistency between risk premiums for state variables that have time series forecasting power on the economic activity. We follow an alternative path that we consider more informative about the true nature of economic uncertainty, as explained in what follows.

uncertainty is different from risk in the sense that it is linked to *unexpected movements* within a given system, and therefore, it is more informative to treat it as an *economic regime*, instead of as a risk factor.

In this respect, the literature in macroeconomics has made important advances in recent times regarding the construction of more appropriate measures of uncertainty that take into account precisely its different nature with respect to risk. Some measures are a direct estimation of unexpected variations within a given system (Jurado et al., 2015; Chuliá, et al. 2017b), while some others have resorted to a less probabilistic approach, based on a direct search for uncertainty-related key words in the media (Baker et al., 2016). The latter approach is more compatible with the original *Knithian* or *fundamental* view of uncertainty (Knight, 1921), because it does not rely directly on a probabilistic estimation for constructing the measure. For this and other reasons that we will explain later on we used the index by Baker et al. (2016) in our calculations.

Our model considers two extreme states: one of *low* uncertainty and one of *high* uncertainty. We model endogenously the probability of transition between the two states in a smooth fashion. Thus, we think of excess returns and their explanatory factors as being between these two states in every period, with a different probability associated to each state. As mentioned before, the only time-varying beta in our specification is the one related to momentum. We do so because momentum can be understood as an extrapolation of past behavior to predict the future and, uncertainty is related precisely with the difficulty of assigning an accurate probability to future events based on the past. If investors are using past return realizations to construct such a probability, as they are presumably doing in the case of momentum, we expect them to behave sharply different in low economic uncertainty and high economic uncertainty environments. In this way, we show that it is possible to get one step closer to the interpretation of uncertainty as an economic state and to highlight its difference with risk.

Notice that we are assuming that invertors observe or are sensitive to the level of uncertainty in the market. This fact, in turn, determines the betas accompanying momentum in the equity premium equation. In other words, a change in the uncertainty variable will produce a smooth switch in the momentum factor's beta. This change might occur *joint to* a change in the unconditional probability distribution of momentum. We explore the two possibilities here, changes in the momentum beta and changes in the probability distribution of momentum itself. One way in which uncertainty may affect momentum is because of the adaptive nature of momentum portfolios. That is, investors use immediate events in the past to estimate the parameters that govern future probability outcomes regarding momentum[6]. We acknowledge that it well might be the case for the other parameters in the system to depend on the uncertainty regime as well. Nevertheless, we prefer to follow a more conservative path and focus on the momentum effect, and its probability distribution, which by construction are subject to the kind of reasoning exposed above.

We analyzed 25 value-weighted portfolios sorted according to momentum and size, 100 portfolios sorted according to size and book to market (B/M), and four univariate portfolios

[6] In a way that certainly resembles the adaptive learning models explained for example in Evans and Honkapoia (2001) and Branch and Evans (2011).

according to size, B/M, profitability and investment. As highlighted before and as expected, we found that momentum lacks relevance in regimes of high uncertainty for most of the portfolios analyzed, just when extrapolating past unclear patterns does not seem as a clever strategy. One exception being those portfolios that are highly exposed to the momentum factor even during low uncertainty regimes, and therefore that within investors' minds can be said to have confirmed past performance expectations beyond doubt. This is consistent with the understanding that when uncertainty is high, investors' task of constructing accurate estimations of the probability distribution that governs stock returns becomes more challenging.

With the state probabilities in hand, we constructed pricing errors and goodness of fit statistics for each model: the three-factor model and the five-factor model, with and without momentum, and for each regime, low and high uncertainty. We also compare those with linear specifications of the models, which include and do not include momentum[7]. Then, we analyze the evolving nature of momentum and some of their statistical features relevant for investors, such as kurtosis and skewness. We found that pricing errors are smaller in high uncertainty regimes, for portfolios that include momentum as a factor, but also that abnormal returns of momentum above the other factors in the model *vanish* in high uncertainty regimes. Moreover, momentum kurtosis *doubles*, skewness becomes *negative* and the Sharpe ratio virtually *goes to zero* in high uncertainty states, making momentum trading particularly risky and unprofitable in these situations.

2. Methodology: A conditional factor model

Our main method is an adaptation of the smooth transition regression (STR) model due to McAleer and Medeiros (2008)[8] and Hillebrand et al. (2013)[9]. This framework is particularly well suited for our purposes. It allows us to condition momentum betas and pricing errors on the level of uncertainty, and to present the results as arising from two extreme states in the market, which eases the exposition. Nevertheless the model assumes that the transition between the states is smooth, as is presumably the case in practice, but includes abrupt switches between the states as a special case, which is also attractive. Unlike us, the original authors use their model to estimate conditional volatilities of several returns of stock market indices in the global economy, using lagged variables to condition the transition. In what follows we describe a specialization of the general model that transits between two extreme regimes, which are related to *low* and *high* uncertainty in the economy. We estimate two factor models, a five-factor model proposed by Fama and French (2015) and a three-factor model by Fama and French (1993), which are crucial benchmarks in the financial literature.

---

[7] When the three-factor model includes momentum is of course Carhart's (1997) model.

[8] The authors named it HARST, multiple-regime smooth transition heterogeneous autoregressive. In our case we do not consider autoregressive terms because there are not theoretical insights about their inclusion.

[9] Variations of the same model have been employed in Hillebrand and Medeiros (2016) and Fernandes et al. (2014).

Fama and French (2015) propose the following equation, which is also our main benchmark here:

$$R_{it} - R_{Ft} = \alpha_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}. \quad (1)$$

In this equation excess returns of portfolio i above the risk-free rate, respond to the traditional *market*, *size*, and *B/M* risk factors through the coefficients b_i , s_i and h_i respectively. Equation 1 has been extended to include two proxies for profitability and investment with exposures measured by r_i and c_i. R_{Mt} is the return on the value-weighted (VW) market portfolio, SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks. HML_t is the difference between the returns on diversified portfolios of high and low B/M stocks. RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA_t is the difference between the returns on diversified portfolios of the stocks of low and high investment firms (see Fama and French (2015) for details on the factors' construction). Now consider equation 2 augmented with a momentum factor, in the context of a time-series regression:

$$R_{it} - R_{Ft} = \alpha_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t \dots$$

$$\dots + m_i MOM_t + e_{it}, \quad (2)$$

in the RHS we find an intercept, the exposure to the six factors b_i, s_i, h_i, r_i, c_i, m_i, as described before and a residual, which is assumed to be random noise. This can be expressed in a more compact way as follows:

$$EP_{it} = \mathbf{X_t}'\boldsymbol{b_i} + e_{it}, \quad (3)$$

where $EP = R - R_F$ is the equity premium, $\mathbf{X_t}$ is a $T \times (k+1)$ matrix containing the explanatory factor returns in the RHS, k is the number of factors, in this case 6. $\boldsymbol{b_i}$ is a $k \times 1$ vector that contains the intercept of the regression and the exposures to each factor.

The generalization of equation 3 to a STR framework with two limiting regimes is as follows:

$$EP_{it} = G(\widetilde{\mathbf{X}}_{\boldsymbol{t}}; u_t; \boldsymbol{\psi_i}) + \mathbf{W_i}'\boldsymbol{b_{wi}} + \tilde{e}_{it}, \quad (4)$$

where $G(\widetilde{\mathbf{X}}_{\boldsymbol{t}}; u_t; \boldsymbol{\psi_i})$ is a nonlinear function of the switching- variables $\widetilde{\mathbf{X}}_{\boldsymbol{t}}$, which contains a constant and the momentum factor, and u_t is the transition variable that governs the switching between the two regimes (namely the uncertainty index). There is also $\boldsymbol{\psi_i}$ that groups the parameters associated to G and $\mathbf{W_i}$, which is a $T \times 5$ matrix containing the factors with linear (non-switching) exposure and their associated coefficients $\boldsymbol{b_{wi}}$. Finally, $\tilde{e}_{it}$ is a vector of random noise residuals. This model can be further specialized as follows:

$$EP_{it} = \widetilde{\mathbf{X}}_{\boldsymbol{t}}'\boldsymbol{b_{0i}} + \widetilde{\mathbf{X}}_{\boldsymbol{t}}'\boldsymbol{b_{1i}} f(u_t; \gamma_i, c_i^*) + \mathbf{W_i}'\boldsymbol{b_{wi}} + \tilde{e}_{it}, \quad (5)$$

where $f(u_t; \gamma_i, c_i^*)$ is the logistic function given by:

$$f(u_t;\gamma_i,c_i^*)=\frac{1}{1+e^{-\gamma\left(u_t-c_i^*\right)}}\,, \tag{6}$$

here γ is the *slope* parameter and c^* can be understood as a *threshold* value that needs to be estimated as well. Notice that $f(u_t;\gamma_i,c_i^*)$ is monotonically increasing in u_t and therefore $f(u_t;\gamma_i,c_i^*)\to 1$ as $u_t\to\infty$ and $f(u_t;\gamma_i,c_i^*)\to 0$ as $u_t\to -\infty$. For this reason $\boldsymbol{b_{0i}}=\left[b_{0i}^{\alpha},b_{0i}^{MOM}\right]$ is to be thought of as containing the linear exposure of the excess returns to the momentum factor (and the intercept) during a *low uncertainty* regime, while $\boldsymbol{b_{0i}}+\boldsymbol{b_{1i}}$ is the exposure to the momentum factor (and the intercept) in an extreme *high uncertainty* regime.

When $\gamma_i\to\infty$, the logistic function becomes a step function, and the model converges to a threshold specification, for this reason γ_i is known as the slope parameter and it determines the speed of the transition between the two limiting regimes. The variable u_t is called the *transition variable*, and it is a measure of uncertainty in our case. Hence, the level of uncertainty determines the exposure to the risk embedded by the momentum factor.

Two interpretations of the STR model are possible. On the one hand, the model can be thought of as a regime-switching model that allows for two regimes, associated with the extreme values of the transition function, $f(u_t;\gamma_i,c_i^*)=0$ and $f(u_t;\gamma_i,c_i^*)=1$, where the transition from one regime to another is smooth. On the other hand, the STR model can be said to allow for a continuum of regimes, each associated with a different value of $f(u_t;\gamma_i,c_i^*)$ between 0 and 1. We will follow the former interpretation.

3. Data

All the data used in this study, but the economic policy uncertainty index, was retrieved from Keneth French's web page[10]. The uncertainty index is due to Baker et al. (2016) and it is available online at http://www.policyuncertainty.com/. Our estimations regarding the stability of the factor models (Table 1) used a sample of 641 months running from July 1963 to November 2016. This is the longest span available for the five factors in K. French's data-library. The rest of our estimations come from a sample period that starts in January 1985 and ends in November 2016, for a total of 383 months. In this case, the time span is determined by the availability of the economic policy uncertainty index.

Our main data are monthly returns of 25 VW portfolios sorted according to size and momentum. We also used 100 VW portfolios sorted by size and book to market, and 10 portfolios sorted according to each of the following criteria: size, B/M, investment and operating profitability. The regressors (the factors) and the risk-free rate in our models proceed as well from the same source.

We do not provide summary statistics of the factor-portfolios (RHS) or the portfolios returns on the LHS, since they are well known in the literature and have been extensively documented elsewhere, for example in Fama and French (2015, 2016) and Baker et al. (2016), the latter in the case of the uncertainty index.

[10] Available online at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

4. Results

We parse our results in five groups: In section 4.1 we present the results regarding the evolving nature of both, *momentum betas* (4.1.1) and *pricing errors* (4.1.2), when explaining 25 size-momentum portfolios, which are the main target of our contribution. In section 4.2 we present pricing errors of a simpler version of the model, and comparative statistics of the momentum factor in the two regimes of economic uncertainty. Section 4.3 reports results that employ 100 size and book to market portfolios, well known in the field and therefore a relevant benchmark. This is labeled as the case when momentum is not a determinant factor. Section 4.4 seeks to specialize our knowledge about the documented facts related to momentum, using univariate sorts, which help to clarify the role of momentum at explaining the equity premia of big and small size portfolios. Lastly, in section 4.5 we document changes in the 'unconditional' distribution of momentum (that is, in the *momentum moments*) according to the level of uncertainty.

4.1. The evolving nature of momentum for asset pricing

We conducted an exploratory analysis of the parameters' time stability in the three-factor and five-factor models by Fama and French (1993, 2015). The results are reported in Table 1. We estimated 10 different stability tests for each of the 25 portfolios in our sample, thus we ended out with 250 statistics and their respective critical values. To ease the exposition of the results Table 1 only reports the mean, maximum, minimum and standard deviation, across the 25 portfolios, of each set of statistics. More importantly, it shows the number of rejections of the null hypothesis, which is in all the cases parameter stability. The 10 statistics employed were: three based on the cumulative sum of the residuals, the recursive residuals and the scores, labeled OLS-cusum, Rec-cusum, and Score-cusum respectively. Two tests RE and ME, which are constructed using recursive OLS estimates of the regression coefficients or moving OLS estimates respectively. The test provided by Nyblom (1989) and Hansen (1992a; 1992b) and a recursive Chow statistic (Chow, 1960; Andrews and Ploberger, 1994). Finally, we also employed three procedures based on F-statistics: SupF, AveF and ExpF.[11]

[11] These sorts of procedures are well documented, for instance in Zeileis (2005) or in the accompanying documentation of 'struchange' package in the statistical software R that was used to carry out the estimations (Zeiles, 2006).

Table 1. Structural change tests: We used 10 tests of structural change seeking for possible instabilities in the 5 Factor Model (Panel A) and the 3 Factor Model (Panel B). In most of the cases (with the only exceptions of two cusum tests) the null hypothesis of parameters stability is rejected most of the times. We used 25 value-weighted portfolios sorted by momentum and size. Our sample for these estimations runs from Jul:1963 to Nov:2016. Similar results, which are not reported, were obtained using a reduced sample from Jan:1985 to Nov:2016. Rec-Cusum, Ols-Cusum and Score-Cusum are based on cumulative residuals of recursive, ols or score estimations. RE and ME are based on recursive ols estimates of the regression coefficients or moving ols estimates respectively. Chow and Nyblom-Hansen correspond to the statistics proposed by those authors. SupF, AveF and ExpF are tests of structural change based on F-statistics.

Panel A: Five Factor Model

Test	*Rec-Cusum*	*Ols-Cusum*	*Score-Cusum*	*Chow*	*Nyblom-Han.*
Mean	0.543	1.030	1.729	5.649	2.500
Max	0.936	1.840	2.308	15.288	3.701
Min	0.177	0.332	0.296	3.032	0.592
Stad. Dev.	0.250	0.334	1.192	1.076	1.411
Null Rejections	**0**	**4**	**12**	**22**	**19**

Test	*SupF*	*AveF*	*ExpF*	*RE*	*ME*
Mean	57.303	32.813	24.730	3.189	2.076
Max	121.039	86.386	55.310	5.012	2.978
Min	22.423	14.799	10.987	0.971	0.347
Stad. Dev.	28.477	10.808	10.257	1.423	1.574
Null Rejections	**25**	**24**	**25**	**23**	**25**

Panel B: Three Factor Model

Test	*Rec-Cusum*	*Ols-Cusum*	*Score-Cusum*	*Chow*	*Nyblom-Han.*
Mean	0.533	1.170	1.928	9.767	2.568
Max	0.913	2.270	2.720	24.267	4.110
Min	0.158	0.383	0.304	5.355	0.659
Stad. Dev.	0.249	0.647	1.439	1.262	1.566
Null Rejections	**0**	**7**	**21**	**23**	**24**

Test	*SupF*	*AveF*	*ExpF*	*RE*	*ME*
Mean	65.455	34.768	28.775	3.174	2.502
Max	127.016	91.054	59.838	5.045	3.797
Min	26.121	16.944	12.814	0.872	0.627
Stad. Dev.	24.979	9.733	7.872	1.429	1.559
Null Rejections	**25**	**25**	**25**	**24**	**25**

As can be noticed, except for two out of three cusum-tests, the tests show evidence in favor of unstable coefficients, with a number of null rejections above 12 and, most of the time, above 20 (out of 25 portfolios). Interestingly, but as expected, the three-factor model houses a greater number of rejections of the linearity specification following almost all the tests. Therefore, the new factors (investment and profitability) add to the explanation in a way in which non-linearity of the portfolios reduces. Yet, after observing the last row of Panel A, we can conclude that even talking about the five-factor model, a non-linear behavior continues being an issue.

The tests shown above offer an intuitive approach to parameter instability issues in the context of beta-pricing representations of the equity premium as the ones provided by the two Fama-French models analyzed here. Nevertheless, they are also overly general to our purposes. That is, they target all the coefficients in the model, even those that are theoretically or intuitively linked to a linear representation of the stochastic discount factor (such as the market factor). We are more interested here in the momentum factor, which is not that theoretically grounded and linked to such a linear representation.

For the aforementioned reason, we conducted linearity tests that specifically compare the null hypothesis of linearity with a non-linear process governed by a logistic function, in the same spirit of the STR model explained in the methodology (section 2). In this case, we only allowed for non-linearity of the intercept and the coefficient that measures exposure to momentum. Notice that this is a very stringent requirement, because we assume constancy of the other parameters, which explain a big share of the total variation in the equity premium. Even in this case we document evidence of non-linearity in more or less half of the 25 portfolios at both 90% and 95% levels of confidence[12].

In Table 2 we report the average values of the statistics in each quintile of the size distribution of the portfolios, their standard deviation and the number of null rejections at both, 5% and 10% significance levels. The highest number of rejections, for both the five-factor and the three-factor models, are recorded in the 4th quintile of the size distribution (the null is rejected 4 out of 5 times in the former case and 5 in the latter). Otherwise the non-linear behavior seems uniformly distributed across the size quintiles.

[12] McAleer and Medeiros (2008) explore the same significance levels in their simulations 0.05 and 0.1. They used financial daily data, with very well-known characteristics of leptokurtosis, non-normality, breaks, asymmetric responses to shocks, etc., so we think that in our case a higher significance level would be justified, conducting to more rejections of the linearity hypothesis. Nevertheless, we prefer to report these more conservative values. For the other portfolios analyzed the number of rejections is even higher. In what follows we also show the significance of the changes using t-statistics.

Table 2. Smooth transition linearity test: We test for linearity of the momentum coefficient that measures the effect of momentum on the equity premium ($R_i - R_f$) both, in the five-factor model (Panel A) and the three-factor model (Panel B). The null hypothesis of linearity is tested against the alternative of a logistic function that maps a smooth transition from a "low uncertainty" regime to a "high uncertainty" regime. We used 25 value-weighted portfolios sorted by momentum and size. Our sample for these estimations runs from Jan: 1985 to Nov: 2016, that is, the period for which the political uncertainty index of Baker et al. (2016) is available. The table shows the average of the statistics and the standard deviation in each case. The last two columns show the number of null rejections for each quintile in the portfolios sorted by size. In approximately half of the cases the linearity of the effect is rejected at both 90% and 95% levels of confidence, in all the quintiles.

Panel A : Five Factor Model

	Statistic average value	*Standard deviation*	*Null rejections 90%*	*Null rejections 95%*
Small	1.685	1.251	2	1
2	1.821	1.302	2	2
3	1.954	1.168	2	2
4	3.175	1.126	4	4
Big	1.869	1.691	1	1
Average/total	2.101	1.308	11	10

Panel B : Three Factor Model

	Statistic average value	*Standard deviation*	*Null rejections 90%*	*Null rejections 95%*
Small	1.997	1.283	2	2
2	2.767	1.344	4	2
3	3.130	2.104	3	3
4	4.483	2.499	5	4
Big	2.818	2.446	3	3
Average/total	3.039	1.935	17	14

Motivated by the results in tables 1 and 2 we estimated the model presented in equations 3 to 5 using each of the 25 portfolios. We aim to describe the non-linear behavior of the momentum factor according to the level of economic uncertainty. The descriptive statistics of slope, γ, and threshold, c^*, parameters are reported in table A1 of the appendix. The average value of the threshold parameter, which determines the transit from low to high uncertainty regimes is 101.38 and this means that more or less half of the time (49.09%) the model assigns (in average) the observation to a high uncertainty regime, while the other half the model assigns more probability to the occurrence of a low uncertainty regime. Nevertheless, this parameter varies across portfolios. The estimation of the beta coefficient in each case follows the idiosyncratic estimates that correspond to each portfolio.

Figure 1 shows the uncertainty index from January 1985 to November 2016 and emphasizes the high uncertainty regimes using gray areas. As can be observed, these gray areas of high economic uncertainty match documented historical episodes such as economic recessions (1987), bubble inflation and subsequent bursts and market crashes (1987, 2000-2002, 2007-2008), and financial and economic turmoil episodes (2009-2011). Notice as well that there are also high uncertainty episodes that are not related to ‘bad’ economic conditions. Consider for instance the high-tech revolution of early-mid 1990s, which is identified in our model (in average) as a high uncertainty state. In the words of Segal et al. (2015, p. 117) “with the introduction of the world-wide-web, a common view was that this technology would provide many positive growth opportunities that would enhance the economy, yet it was unknown by how much?” These authors refer to such episodes as ‘good’ uncertainty states.

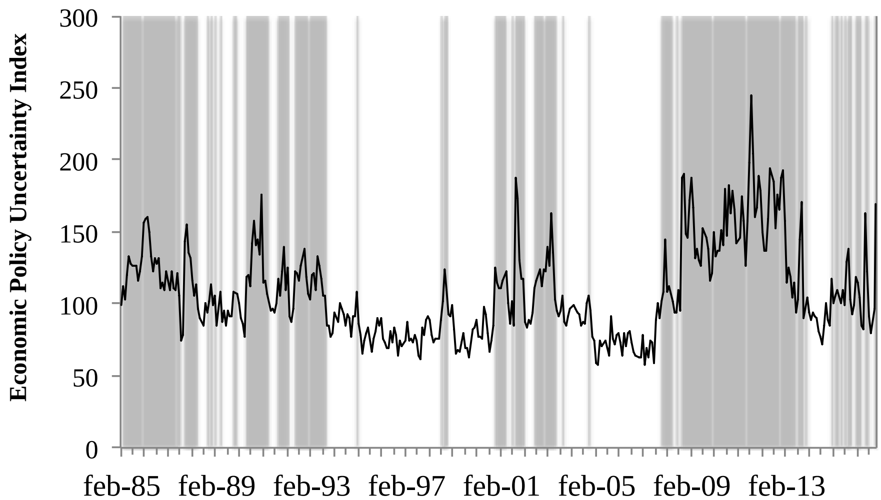

Fig. 1 Economic policy uncertainty index and regimes of low and high uncertainty: The figure plots the index by Baker et al. (2016) and the average-regimes of low and high uncertainty. The threshold value separating the two regimes was estimated as the average of the threshold estimates in each of the 25 five-factor models, fitted to 25 value weighted portfolios sorted by size and momentum. The sample period is Jan: 1985 – Nov: 2016. High uncertainty regimes are related to crises and recessions in the world and the US economies, but also to good uncertainty episodes as the high-tech revolution of early-mid 1990s. Half of the sample (49.09%) is assigned to a high uncertainty state in our sample (in average) using the estimate 101.38 of $c*$ (Table A1 of the appendix).

Our model captures both ‘good’ and ‘bad’ uncertainty episodes and in doing so it takes distance from the extant literature that relates momentum profits with god or bad *economic states* (Cooper et al., 2004)[13]. The model correctly identifies these periods albeit not for all

[13] We conducted preliminary regressions using the macro-uncertainty indicator of Jurado et al. (2015) alike. This index is available in S. Ludvigson’s web page: www.sydneyludvigson.com, from 1963:Jul to 2016:Jun. We observed that unlike the index by Baker et al (2016), this indicator is almost invariantly related to “bad uncertainty episodes” and it seems insensitive to “good uncertainty shocks”. Thus, when we analyze the effects of momentum on the returns of the 25 size-momentum portfolios, the *market state* effect, as documented by Cooper et al. (2004), prevails and momentum betas experience a *negative change* in most of the cases under high uncertainty regimes. We think that this exercise is illustrative about the difference (but also about the relationship) between the effects of *macro-uncertainty* (both good and bad) and the effects induced by *market states,* on momentum prices.

the portfolios the high uncertainty regime necessary occurs at the same time. Regarding the slope parameter there is a significant dispersion of the estimates, which means that while for some models the change from the low uncertainty regime to the high uncertainty regime is very smooth ($\gamma = 9.99$), in other cases it is more abrupt ($\gamma = 547.57$). These asymmetries are also addressed here by conducting separate regressions for each portfolio.

The non-linear estimates of the momentum factor exposures and the pricing errors (the intercepts) are presented in Table 3, columns 1 to 5, joint to their associate t-statistics in columns 6 to 10. We first refer to Panel A, which contains the information regarding the five-factor model. In the first 5 rows are reported the estimates of the intercepts, corresponding to the low uncertainty regime, for each of the momentum (columns) and size (rows) portfolios. That is, the estimates of the parameter b_o^{α} in equation 5. As can be noted, only in 5 cases (out of 25) those intercepts present a t-statistic above 2.0, and therefore, for most of the models they are not statistically different from zero. In the second set of estimates, we found those associated to the momentum exposures (rows 11 to 15, parameter b_o^{MOM}). In this case, the number of t-statistics above 2.0 raises to 22 (out of 25) and that indicates a significant role of momentum explaining the equity premium during low-uncertainty regimes. Most of the coefficients associated to the momentum factor are negative (although many of them are relatively small), the only exception being the high momentum firms (row five, columns from 6 to 10). As expected, the most significant exposures, either negative or positive, are found in the first and the fifth quintile of the momentum distribution.

In rows 11 to 15 and 16 to 20 we can observe the estimates of $\boldsymbol{b_1} = \left[b_1^{\alpha}, b_1^{MOM}\right]$, that is, of the changes in the non-linear parameters, from a low uncertainty regime to a high uncertainty regime. Once again, the changes in the intercept are statistically insignificant most of the time (the only exception being the portfolio in the 3rd quintile at both the size and momentum sorts). The point estimates of such changes are more likely negative (14) than positive (11), despite of the quintiles. In marked contrast, all the changes in the momentum factor are associated to a t-statistic above 2.0. Mostly, the changes are positive, for portfolios in quintiles 3 and 5 (except for the intersections with quintiles 3 to 5 in size) and sometimes they are negative, mostly for portfolios in the first quintile. These results point out to momentum as *the determining factor explaining* the non-linearity documented before, rather than the intercepts.

When we focus on Panel B, which reports the estimates and corresponding t-statistics of the traditional Fama-French three-factor model, the documented behavior remains almost the same. Most of the intercepts are statistically equal to zero, with the same 5 exceptions and 3 in exactly the same portfolios than before. This time the momentum factor is even more important to explain the low-uncertainty equity premia (t-statistics above two, 24 times out of 25). The changes in the momentum exposure are also relevant (t-statistics above 2.0 in 23 cases). The signs and distributions of the changes follow as well the same patterns explained before with relation to the five-factor model.

Table 3. Smooth transition non-linear estimates: The first five columns in the table show the estimates corresponding to the non-linear parameters in our smooth transition model. b_o^{α}, b_o^{MOM} are the estimates associated to the intercept and the momentum factor respectively in the low-uncertainty regime. b_1^{α} and b_1^{MOM} are the estimates of the changes in these parameters from low to high uncertainty states. The last five columns show the associated t-statistics for each parameter (against the null of non-significance). We estimate one model for each portfolio of 25 value-weighted portfolios sorted according to size and momentum. The variable that governs the transition between the two regimes was, in each case, an economic policy uncertainty index. We present the results for both the five-factor model (Panel A) and the three-factor model (Panel B). Our sample runs from Jan: 1985 to Nov: 2016. Standard errors used to construct the t-statistics were corrected for non-normality and heteroscedasticity.

Mom →	*Low*	*2*	*3*	*4*	*High*	*Low*	*2*	*3*	*4*	*High*
Panel A: Five Factor Model										
			b_o^{α}					t(b_o^{α})		
Small	-0.48	-0.10	0.22	0.48	0.56	-1.42	-0.44	**2.20**	**4.62**	**4.11**
2	-0.10	0.19	0.14	0.16	0.52	-1.01	1.28	0.98	1.55	**3.29**
3	0.54	0.05	-0.23	-0.13	0.00	**2.05**	0.33	-1.77	-1.12	0.04
4	-0.04	-0.04	-0.04	0.01	0.05	-0.25	-0.39	-0.37	0.06	0.45
Big	0.21	0.56	-0.05	-0.01	-0.08	1.29	2.17	-0.38	-0.07	-0.89
			b_o^{MOM}					t(b_o^{MOM})		
Small	-0.42	-0.04	-0.14	-0.06	0.19	**-3.86**	-0.56	**-5.76**	**-2.23**	**5.68**
2	-0.71	-0.51	-0.18	-0.05	0.22	**-29.61**	**-11.66**	**-3.98**	-1.73	**4.79**
3	-1.01	-0.42	-0.22	-0.07	0.43	**-13.21**	**-8.74**	**-5.89**	**-2.27**	**18.16**
4	-0.81	-0.35	-0.26	-0.17	0.44	**-20.43**	**-15.82**	**-8.18**	**-3.46**	**20.51**
Big	-0.77	-0.77	-0.30	-0.02	0.47	**-22.67**	**-9.11**	**-6.97**	-0.54	**21.85**
			b_1^{α}					t(b_1^{α})		
Small	0.34	0.04	-0.22	-0.29	-0.18	0.93	0.19	-1.35	-1.75	-0.82
2	0.13	-0.16	-0.07	0.06	-0.33	0.64	-0.96	-0.42	0.46	-1.83
3	-0.43	-0.06	0.41	0.18	0.21	-1.50	-0.35	**2.68**	1.21	1.19
4	0.31	-0.07	0.27	-0.02	-0.22	1.17	-0.36	1.86	-0.13	-0.85
Big	-0.54	-0.36	0.04	-0.08	0.06	-1.34	-1.32	0.22	-0.47	0.33
			b_1^{MOM}					t(b_1^{MOM})		
Small	-0.36	-0.23	0.11	0.20	0.14	**-3.15**	**-2.86**	**3.09**	**5.52**	**2.92**
2	-0.22	0.21	0.12	0.15	0.14	**-5.56**	**4.40**	**2.53**	**4.20**	**2.86**
3	0.23	0.11	0.09	0.21	-0.09	**2.82**	**2.19**	**2.09**	**5.42**	**-2.57**
4	-0.14	-0.12	0.16	0.26	-0.17	**-2.53**	**-3.25**	**4.29**	**5.04**	**-2.94**
Big	-0.23	0.35	0.23	0.17	-0.12	**-2.53**	**4.04**	**5.01**	**3.86**	**-3.52**

Mom →	*Low*	*2*	*3*	*4*	*High*	*Low*	*2*	*3*	*4*	*High*
Panel B: Three Factor Model										
			b_o^{α}					t(b_o^{α})		
Small	-0.59	0.05	0.04	0.49	0.45	**-3.03**	0.52	0.20	**4.77**	**3.69**
2	-0.18	0.28	0.25	0.23	0.45	-1.71	1.78	1.57	**2.21**	**2.79**
3	0.46	0.16	-0.03	0.01	0.00	1.76	0.90	-0.17	0.07	0.05
4	-0.09	0.20	0.27	0.15	0.02	-0.58	1.12	1.64	0.81	0.22
Big	0.18	0.56	0.01	0.06	-0.10	1.18	2.11	0.06	0.42	-1.15
			b_o^{MOM}					t(b_o^{MOM})		
Small	-0.61	-0.27	-0.24	-0.05	0.22	**-11.21**	**-13.89**	**-4.81**	**-2.03**	**8.45**
2	-0.72	-0.58	-0.25	-0.07	0.24	**-29.52**	**-12.08**	**-5.36**	**-2.48**	**5.37**
3	-0.97	-0.50	-0.36	-0.11	0.42	**-12.85**	**-9.83**	**-7.37**	**-3.23**	**18.82**
4	-0.82	-0.59	-0.43	-0.25	0.44	**-20.64**	**-11.02**	**-8.66**	**-4.82**	**20.52**
Big	-0.77	-0.78	-0.35	-0.06	0.47	**-22.93**	**-8.90**	**-7.93**	-1.45	**21.70**
			b_1^{α}					t(b_1^{α})		
Small	0.30	-0.29	0.18	-0.29	-0.60	1.09	-1.28	0.88	-1.73	-1.91
2	0.09	-0.15	-0.05	0.06	-0.37	0.40	-0.82	-0.28	0.42	**-2.04**
3	-0.47	-0.04	0.30	0.20	0.12	-1.61	-0.21	1.65	1.21	0.65
4	0.26	0.00	-0.02	-0.01	-0.24	0.99	-0.02	-0.11	-0.07	-0.93
Big	-0.57	-0.26	0.05	-0.02	0.05	-1.43	-0.92	0.33	-0.09	0.26
			b_1^{MOM}					t(b_1^{MOM})		
Small	-0.25	0.11	0.19	0.19	0.11	**-3.69**	**2.29**	**3.56**	**5.46**	1.57
2	-0.24	0.30	0.23	0.19	0.09	**-5.98**	**5.95**	**4.52**	**5.43**	1.96
3	0.17	0.22	0.26	0.29	-0.11	**2.12**	**4.11**	**5.08**	**7.08**	**-2.94**
4	-0.16	0.27	0.36	0.38	-0.18	**-2.87**	**4.65**	**6.77**	**6.93**	**-3.22**
Big	-0.25	0.37	0.30	0.24	-0.13	**-2.86**	**4.18**	**6.42**	**5.34**	**-3.79**

We also present, in the sake of completeness, in Table A2 of the Appendix the estimates corresponding to the linear exposures to the risk factors in the models (*b, s, h, r, c* in Panel A, and the three former in Panel B). Our estimations agree with what has been previously reported in the literature (Fama and French, 2015) regarding the market and the SMB factors. After the inclusion of the two new factors (operating profitability, RMW, and investment, CMA) and the momentum factor with two regimes, the significance of the HML factor reduces compared to the original three-factor model (more noticeable, for the highest and the lowest quintiles in the momentum distribution). On the other hand, coefficients associated to investment (which measure the difference between aggressive and conservative firms) are almost never significant in our specification. This means that a changing momentum is more relevant to explain these 25 portfolio dynamics than the investment factor.

4.1.1. Momentum betas

In Figure 2 we show the magnitude of the exposure to momentum, under low and high uncertainty regimes. That is, for each portfolio we plotted the coefficient b_o^{MOM} (in black) that measures the effect of momentum on the equity premium, when uncertainty is low, and next to it (in red) we plotted the exposure to momentum under a regime of high uncertainty (that is $b_o^{MOM} + b_1^{MOM}$). We carry out these calculations for our benchmark specifications, the five-factor model (left column of the figure) and the three-factor model (right column). In the two cases, the most exposed portfolios to momentum are those in the first and the fifth quintiles of the momentum category. The former in a negative way, while the latter positively. In-between the two extreme quintiles the momentum exposure increases from losers to winners monotonically. The same pattern is documented as well by Fama and French (2016), and it is expectable from the construction of the momentum portfolios.

What is new here is that with our model fitted to the momentum-size portfolios we are able to document a least two novel patterns to the literature. Focusing in the five-factor model: first, in the high uncertainty regime the betas of the losers become more negative, and the betas of the winners either remain high without increasing[14] (big caps) or increase even more (small-medium) compared to the low uncertainty case. Therefore in most of the cases *momentum effect reinforces in high uncertainty regimes for the extreme quintiles of the momentum-sorted portfolios*. Second, medium size and momentum portfolios (intersections between the 2nd, 3rd and 4th quintiles of both categories) *almost always reduce their exposure to momentum during high uncertainty states* (there are only 3 exceptions out of 15 to this pattern). That is, in the high uncertainty state, most of the betas of the non-extreme momentum portfolios become virtually zero, with changes in the parameter of the same magnitude that the extent of the effects in the low uncertainty regime, but with opposite signs. All in all, it seems that *while momentum loses track for less exposed portfolios during regimes of high economic uncertainty, it gains relevance for the most exposed portfolios*.

The same conclusions hold when we focus on the three factor model (Panel B), if anything changes is that, in this case, there are even fewer exceptions to our second fact. That is, during episodes of *high uncertainty the effect of momentum always reduces* or *reverses* (changes its sign) for medium size portfolios (2nd-4th size-quintiles) intersecting medium levels of exposures to momentum (2nd-4th momentum-quintiles). Once again, momentum effect, whether it is positive or negative, reinforces for the extreme quintiles in the momentum category, apart from big portfolios that depend positively on momentum, and medium-size portfolios that depend negatively on it.

[14] Indeed in two cases they decrease. See the results in section 4.4 regarding univariate sorts for a more detailed explanation regarding this atypical behavior. It seems that while momentum relevance increases for high-momentum portfolios, it decreases for big-size firms. The net result is a reduction in the momentum beta for big caps with high momentum.

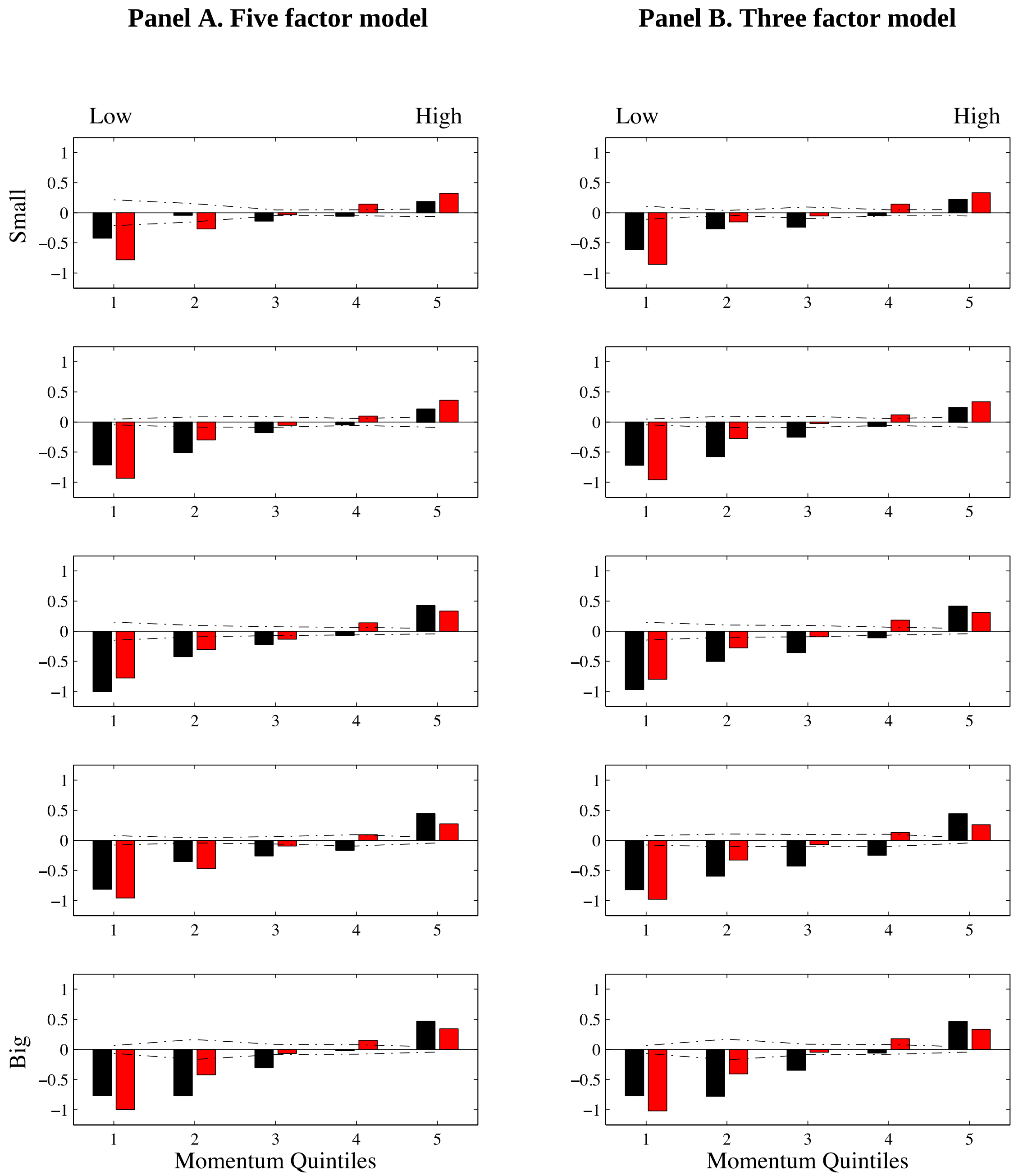

Fig. 2 Changes in the effect of momentum on the equity premium: The figure shows the coefficients associated to momentum in the extreme regimes of "low uncertainty", in black to the left, and "high uncertainty", in red to the right. The dotted line corresponds to 1.96 times the standard error of the momentum coefficient in the linear part of the model, that is, in the low uncertainty regime. Those estimates were obtained using 25 value-weighted portfolios sorted according to size and momentum. Our sample runs from Jan: 1985 to Nov: 2016.

Our results can be rationalized in the following way. During high uncertainty episodes, the behavioral biases of investors operate reinforcing negative or positive perceptions about portfolios or firms' returns that were following a *clear path* during low uncertainty periods. That is, if a stock was doing remarkably bad or remarkably good when uncertainty was low, investors expect this to continue with *lager impulse* during episodes of high uncertainty. Except for medium and big firms very exposed in a positive way to momentum. On the other hand, if a firm's return or a portfolio is not clearly exposed to momentum in either way the market do not assign much weight to this factor during high uncertainty, perhaps because there is not a clear trend to reinforce. Indeed momentum's effect almost disappears or even reverts during high uncertainty regimes for portfolio returns that lacked a clear relationship with the momentum factor in the low uncertainty regime.

Our results are consistent, for instance, with the behavioral models of Daniel et al. (1998), Hong and Stein (1999) and Gervais et al. (2001). Nevertheless, if this is to be the case our results also imply that *investors' biases do not operate with the same intensity under different levels of macroeconomic uncertainty*. This is consistent with the claim of Daniel and Titman (2006) according to which individuals tend to be *particularly* overconfident or overreactive (that is particularly biased) in environments in which more judgment is required to evaluate ambiguous information. This is essentially a high uncertainty regime.

Consider for instance the model by Daniel et al. (1998). These authors assume that not only investors are overconfident about their private information and overreact to it, but also that they have a self-attribution bias. When subsequent wages of information make their way to the news, investors react asymmetrically to the pieces of information that confirm their preconceptions, compared to those that disconfirm them. As a consequence, investors' overconfidence increases after the arrival of confirming news and such a high level of overconfidence fosters the initial overreaction, generating momentum. From our results, it seems that momentum arising from confirming news is more priced by the market under high uncertainty regimes, but only for *remarkable* winners and losers. That is, investors' biases only operate as expected, following the reasoning by Daniel et al (1998), under high uncertainty regimes regarding those portfolios that evidence a stark trend.

The extension of Daniel's et al. (1998) narrative to account for momentum profits across good and bad market states has been carried out by Gervais et al. (2001) and tested, with favorable evidence by Cooper et al. (2004). Notice, however that our 'states' of course are not market states, but uncertainty regimes and that we find evidence of momentum pricing in both of them, although only for the most extreme losers and winners, during high uncertainty periods.

A competing narrative follows from the model by Hong and Stein (1999). This time, the assumption that private information diffuses only gradually through the marketplace is crucial. In Hong and Stein's model there are two sorts of agents, the *news-watchers* and the *momentum-traders*. The news-watchers rely exclusively on a subset of information comprised by their private information, while the momentum-traders resort only to a subset of information contained in past price changes. Clearly, both types of agents display bounded rationality in their own styles. When information diffuses slowly, *some* momentum traders will profit from momentum strategies shortly after substantial news has arrived to the news-watchers, which due to their own bounded rationality underreact to it and fail to push the price until its new fundamental value. This first round of momentum trading creates a further price increase, which sets off more momentum buying, as in a reinforcing loop. Information diffusion is critical because not *all* momentum traders buy during the first round, and of course, only early-momentum traders profit from the strategy imposing a negative externality on late-momentum traders (who buy precisely short before the market corrects to the fundamental value).

Notice that our results imply that either there are *more numerous momentum traders* in high uncertainty regimes, which implies that some news-watchers become suddenly momentum-traders. Or that there are the same proportion of news-watchers and momentum-traders in both regimes, *but* information *diffuses* more slowly when uncertainty is high. Alternatively, you can think as well that actual information contained in the news is more difficult to disentangle from noise in high uncertainty states. If information is slower or more diffused, and investors are particularly anxious about such information,[15] our conjecture is that each wave of information during high uncertainty regimes will produce a more *notorious* and *persistent* reaction on the side of momentum traders, compared to low uncertainty regimes.

This could explain the documented changes in the momentum betas for extreme portfolios. But for most of the portfolios, the slopes of momentum actually *decrease in absolute value* during high uncertainty periods. This suggests that momentum traders only react to very early or very remarkable patterns reinforced by early momentum-traders, under high uncertainty. Otherwise they ignore subtler patterns related to portfolios out of the extreme quantiles. In other words, when uncertainty is high the first significant piece of information that arrives to the news-watchers produces a high reaction on the size of early momentum traders, which in turns will be reinforced by late-momentum traders. But, more diffused pieces of information that fail to produce a clear trend in the prices (median momentum portfolios) are ignored. Our seemly paradoxical results are that high uncertainty does not necessarily imply more *momentum* pricing or trading. Only on particular cases in which winners and losers are more or less obvious (extreme quantiles) momentum increases, otherwise it disappears. Whether such behavior is optimal (we already know it is not fully-rational), we will show soon that it is not. It is precisely in high uncertainty regimes that momentum strategies become riskier and less profitable.

We think that it is more difficult to reconcile our empirical evidence with rational explanations of momentum. Even if a systematic factor could explain momentum as attempted by Ahn et al. (2000) or Yao (2002), you would need to assume that rational agents update somehow their probability assessments in high uncertainty regimes, in a way in which portfolios returns do not react equal to these systematic factors than under low uncertainty. This seems a bit counterintuitive with the notion of fully rational agents, who of course would do any 'update' in mental time, not in real time. This would force the reaction to momentum to be the same under both regimes. Nevertheless, we acknowledge that this discussion is just starting and we only aim to provide some evidence pointing out to the importance of inquiring about the role of uncertainty on momentum strategies.

[15] Cause they need it to forecast the future, which is more difficult to do under high uncertainty.

4.1.2. Intercepts

We now turn to pricing errors, as measured by the intercepts of the regressions.

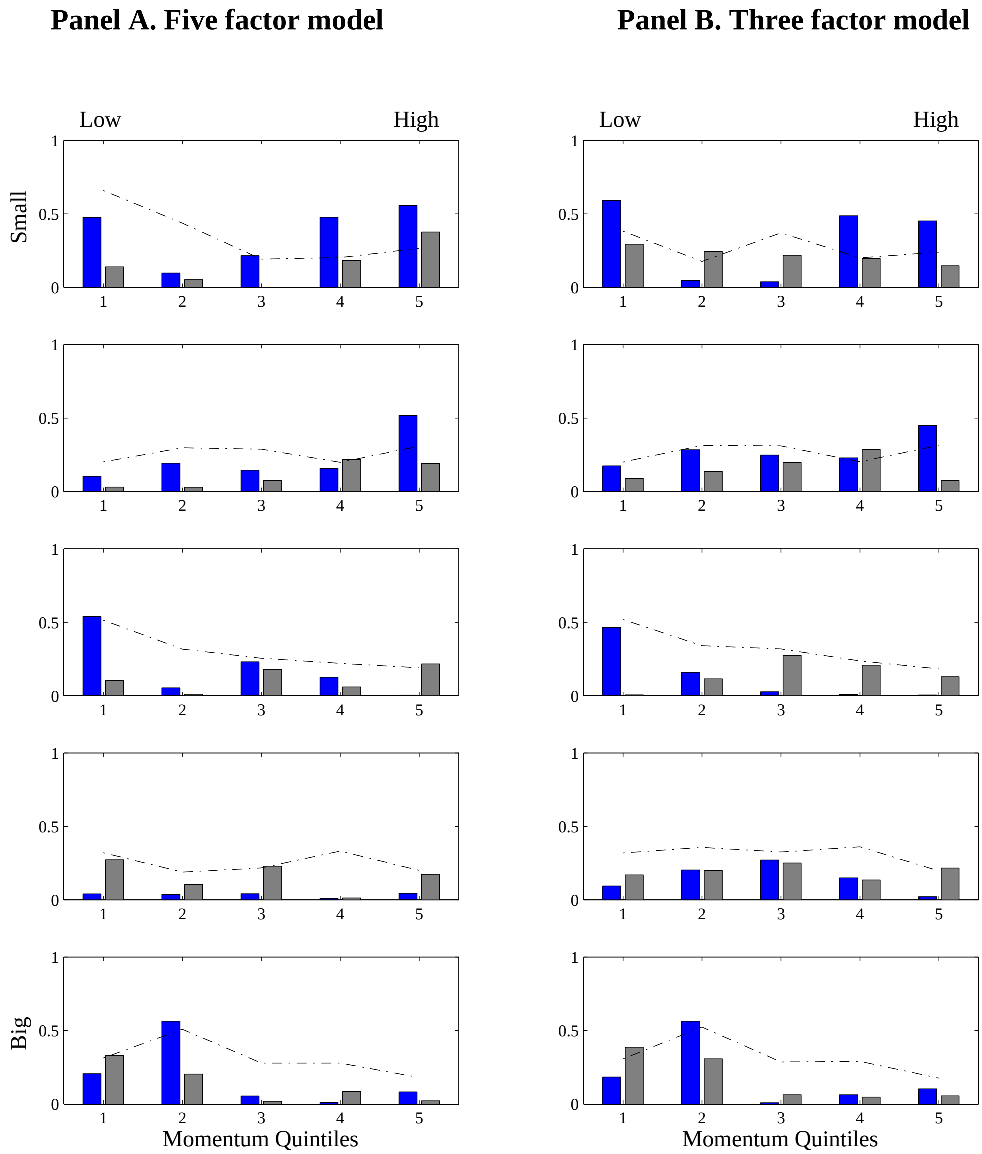

Fig. 3 Changes in the intercept of the model under both regimes: The figure shows the intercepts of the models in the extreme regimes of low uncertainty, gray-bar to the left, and high uncertainty, blue-bar to the right. The dotted line corresponds to 1.96 times the standard error of the intercept in the linear part of the model (i.e. the low uncertainty regime). Those estimates were obtained using 25 value-weighted portfolios sorted according to size and momentum. Our sample runs from Jan: 1985 to Nov: 2016.

Figure 3 shows the intercepts in low uncertainty regimes (left-black bars) and high uncertainty regimes (right-red bars). The figure also displays 1.96 standard errors calculated as in the first regime. In the one hand, in Panel A the general trend is that most of the portfolios show a reduction in their intercepts from low to high uncertainty regimes.

The 4th quintile is the exception to this trend. On the other hand, in Panel B, we observe in general larger pricing errors than in Panel A. We also find greater pricing errors during low uncertainty regimes compared to high uncertainty ones, albeit with a more mixed set of results than in Panel A. We complement this discussion with the estimates in Table 4, section 4.2 in what follows.

4.2. Pricing errors

To complement the discussion in section 4.1 we also calculate pricing errors statistics. Our intention is not to highlight the better performance of the conditional model over the linear one, but to underline how different the *same* three-factor of five-factor model behaves under distinctive regimes of uncertainty, in terms of pricing errors. To make everything comparable with the linear world, we did not use the intercepts exhibited by Figure 3, but instead we estimated a linear model as in equation 2 augmented with two variables: and *indicator variable*, d_{it}^{unc}, indicating whether the probability of the high uncertainty regime in above 0.5, and an *interaction effect* between this indicator and the momentum factor, $int_{it} = d_{it}^{unc} * MOM_t$:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t \ldots$$

$$\ldots + m_i MOM_t + d_i d_{it}^{unc} + i_i d_{it}^{unc} * MOM_t + e_{it}. \quad (7)$$

This simpler version of the model feeds from the probabilities estimated in section 4.1 to define the dummy and the indicator variables. We also have compared it with a model without momentum factor, and with the three-factor model (with and without momentum). With this new set of estimates, comparing the linear world and the two uncertainty regimes is straightforward. We report three statistics in Table 4. For both the 25 VW portfolios sorted by size and momentum (Panel A) and 100 portfolios VW sorted by size and B/M (Panel B) that we will present in section 4.4. The first column of Table 4 indicates the factors included to construct the three statistics that are reported in the table for the linear model (column 2), the high uncertainty regime (column 3) and the low uncertainty regime (column 4).

First, Table 4 exhibits $A|a_i|$, which is the average of the absolute value of the intercepts in each regime and in the linear specification. The second set of estimates in the table shows $A|a_i|/A|\tilde{r}_i|$, which was calculated as the average of the absolute value of the intercepts in each regime and then divided by the average of the absolute value of $\tilde{r}_i$. $\tilde{r}_i$ is the dispersion of the equity premium *temporal means* around their *cross-sectional mean*. That is, we calculated the temporal means for each equity premium series and we defined it as $\bar{r}_i = \sum_T ep_{it}/T$. Here we determine T according to the number of observations in each regime and in the total sample. Then, we subtracted from each $\bar{r}_i$ the cross-sectional mean: $\bar{\bar{r}} = \sum_N \bar{r}_i/N$, such that $\tilde{r}_i = \bar{r}_i - \bar{\bar{r}}$. Finally, Table 4 reports $A(a_i^2)/A(\tilde{r}_i^2)$, this is the average squared intercept over the average squared value of $\tilde{r}_i$ corrected for sampling error in the numerator and denominator. We calculated $A|a_i|$ in the low uncertainty regime, as the averaged-absolute value of the intercepts in such regression, and $A|a_i|$ in the high uncertainty regime, as the averaged-absolute value of the same intercepts plus i_i. We also constructed separate series of $\tilde{r}_i$ for high and low uncertainty regimes, according to the probability $f(u_t;\gamma,c)$. When $f(u_t;\gamma,c) > 0.5$ we classified the observation in such month as belonging to a high uncertainty regime. On the contrary, $f(u_t;\gamma,c) \leq 0.5$ indicates a month of low uncertainty.

In general, the pricing errors are larger in the low uncertainty regime than in the high uncertainty regime, which confirms our analysis from Figure 3. Comparing the linear model with the non-linear estimates we found that the linear model always houses smaller pricing errors in average than the low uncertainty regime and it is even with the high uncertainty regime. What this means is that actual pricing errors are bigger when uncertainty is low of what the linear model says, but also that changes in pricing errors are negative when the market goes from a low to a high uncertainty state. When we compared the second set of statistics we see that the five-factor model plus momentum captures 34.40% of excess return variations under high uncertainty and 56.90% when uncertainty is low. When we remove momentum from the RHS this reduces to capturing nothing in the low uncertainty regime (the statistic is greater than one) to capture only 30% under high uncertainty. The panorama is even worst for the three-factor model in the low uncertainty state, but surprisingly this model outperforms the model with the two additional factors (profitability and investment) under the high uncertainty regime, when there is not momentum. Hence, in this case, these factors seem redundant. The same analysis can be carried out using the last statistic $A(a_i^2)/A(\tilde{r}_i^2)$, so we do not repeat it here.

When we turn to Panel B in the table we note the same patterns than before, with the exception that now the average-intercept is always smaller in the linear world. Although this might seem puzzling at a first glance, because one would naively expect this intercept to be in-between the intercepts of the two uncertainty states, this is not the case. It is well possible for the linear model to exhibit an average intercept bellow both, the low uncertainty regime and the high uncertainty regime. What it means, is not some sort of superiority of the linear model, but instead that in average the value of the intercepts in the linear specification conceals pricing errors that are actually larger, but with different sings, in each of the two uncertainty regimes. Sometimes the linear model overprices and sometimes it underprices some of the portfolios, and as a result, part of the errors cancel out when the intercept is estimated. Finally we also noted that the performance of the five-factor model is less satisfactory in our sub-sample and for the 100 portfolios compared to what has been reported using a longer sample and other portfolios in the LHS, as the ones included in Fama and French (2015).

In short we could extract from this exercise some interesting facts: first, momentum is always a relevant factor, thus momentum puzzle is not over, if anything, we provide fresh evidence on its importance at both high and low uncertainty regimes. Second, the three-factor model *without* momentum performs better than the five-factor model *without* momentum during high uncertainty episodes for the 100 portfolios, so at least for this alignment the factors operating profitability and investment seem redundant, *unless* investors are willing to include momentum in their RHS variables as well. Third, pricing errors are smaller in regimes of high uncertainty. This last finding may be related to the fact that asset prices behave very differently on days when important macroeconomic news is scheduled. Indeed, on announcement days, return patterns are much easier to reconcile with standard asset pricing theories, not only in the cross-section, but also over time (Savor and Wilson, 2014). We may think of high uncertainty episodes as regimes in which important macroeconomic news are more *numerous*, and somehow more *important* (investors are thirsty for information to form their expectations) and thus, factor models fit better to the data[16].

Table 4. Pricing error comparisons between regimes and model: Table 4 shows the statistic $\frac{A|a_i|}{A|\tilde{r}_i|}$. $A|a_i|$ is the average of the absolute value of the intercepts in each regime. $A|\tilde{r}_i|$ is the average of the absolute value of $\tilde{r}_i$. $\tilde{r}_i$ is the dispersion of the equity premium *temporal means* around their *cross-sectional mean*. $A(a_i^2)/A(\tilde{r}_i^2)$ is the average squared intercept over the average squared value of $\tilde{r}_i$. We estimated a nesting model as:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t \dots$$

$$\dots + m_i MOM_t + d_i d_{it}^{unc} + i_i d_{it}^{unc} * MOM_t + e_{it}.$$

Where d_{it}^{unc} indicates whether the probability of the high uncertainty regime in higher than 0.5. We calculated $A|a_i|$ in the low uncertainty regime as the averaged-absolute value of a_i and $A|a_i|$ in the high uncertainty regime, as the averaged-absolute value of $a_i + i_i$.

Factors	Linear	Low Uncertainty	High Uncertainty
Panel A. 5X5 size-momentum portfolios			
		$A\|a_i\|$	
(RM-RF)+SMB+HML+RMW+CMA+MOM	0.115	0.198	0.133
(RM-RF)+SMB+HML+MOM	0.138	0.213	0.178
(RM-RF)+SMB+HML+RMW+CMA	0.217	0.379	0.216
(RM-RF)+SMB+HML	0.302	0.438	0.194
		$A\|a_i\|/A\|\tilde{r}_i\|$	
(RM-RF)+SMB+HML+RMW+CMA+MOM	0.536	0.656	0.431
(RM-RF)+SMB+HML+MOM	0.643	0.672	0.497
(RM-RF)+SMB+HML+RMW+CMA	1.006	1.252	0.701
(RM-RF)+SMB+HML	1.401	1.383	0.543
		$A(a_i^2)/A(\tilde{r}_i^2)$	
(RM-RF)+SMB+HML+RMW+CMA+MOM	0.313	0.512	0.166
(RM-RF)+SMB+HML+MOM	0.4	0.392	0.183
(RM-RF)+SMB+HML+RMW+CMA	0.952	1.347	0.464
(RM-RF)+SMB+HML	1.94	1.55	0.261
Panel B. 10X10 size-book to market portfolios			
		. $A\|a_i\|$	
(RM-RF)+SMB+HML+RMW+CMA+MOM	0.142	0.249	0.214
(RM-RF)+SMB+HML+MOM	0.157	0.273	0.232
(RM-RF)+SMB+HML+RMW+CMA	0.163	0.296	0.224
(RM-RF)+SMB+HML	0.176	0.31	0.245
		$A\|a_i\|/A\|\tilde{r}_i\|$	
(RM-RF)+SMB+HML+RMW+CMA+MOM	0.91	0.899	0.504
(RM-RF)+SMB+HML+MOM	0.999	0.891	0.592
(RM-RF)+SMB+HML+RMW+CMA	1.036	1.07	0.523
(RM-RF)+SMB+HML	1.124	1.003	0.624

16 Hiller et al. (2014) document the importance of media driving momentum profits. Basically their results point out to overreacting and overconfident biases reinforced by media coverage, which is consistent with our narrative.

	$A(a_i^2)/A(\tilde{r}_i^2)$		
(RM-RF)+SMB+HML+RMW+CMA+MOM	0.715	0.726	0.2825
(RM-RF)+SMB+HML+MOM	0.886	0.762	0.371
(RM-RF)+SMB+HML+RMW+CMA	0.877	0.977	0.322
(RM-RF)+SMB+HML	1.145	0.938	0.432

4.3. Momentum price for size and book to market portfolios. The case when momentum is not a determinant factor.

Now we turn our attention to a different sort of portfolios that are not constructed pointing out specifically to the momentum anomaly. We used 100 VW portfolios, sorted on size and B/M dimensions. We do not report linearity-test results in this case, but they indicate that in the case of the five-factor model, roughly 43% (33%) of the portfolios present evidence against linearity in the momentum factor, and the rejections arise to 59% (46%) for the three-factor model, at 90% (95%) level of confidence. That is, evidence in favor of the logistic specification of the STR model employed here.

Figure 4 summarizes the main findings related to this new set of estimates. We only report estimates for the five-factor model, because not much additional insights can be extracted from comparisons with the three-factor model, in this case. The figure indicates that momentum is remarkably more important under low uncertainty regimes than it is during high uncertainty regimes. This is the case in 8 out of 10 deciles of the book to market portfolios. Only for portfolios with high book to market ratios (value stocks in BM9 and BM10) the situation reverses, particularly for BM10, with a less clear pattern for BM9. This finding confirms our first intuition, regarding the 25 portfolios sorted by momentum and size. Since momentum is a relevant, but not a fundamental factor at explaining the dynamics of excess returns for portfolios sorted according to size and B/M, one may expect such behavior to align with that of the median portfolios analyzed before (from 2nd to 4th quintiles in both momentum and size categories of 25 portfolios).

In other words, we confirm that *when momentum is not a first order factor at explaining excess returns in low uncertainty regimes, it loses importance during high uncertainty regimes*. Value stocks are the exception because indeed they are known to be negatively associated to momentum. We talk here about “importance” making reference to the absolute value of the betas associated to momentum, which as can be seen in the plot might be negative or positive.

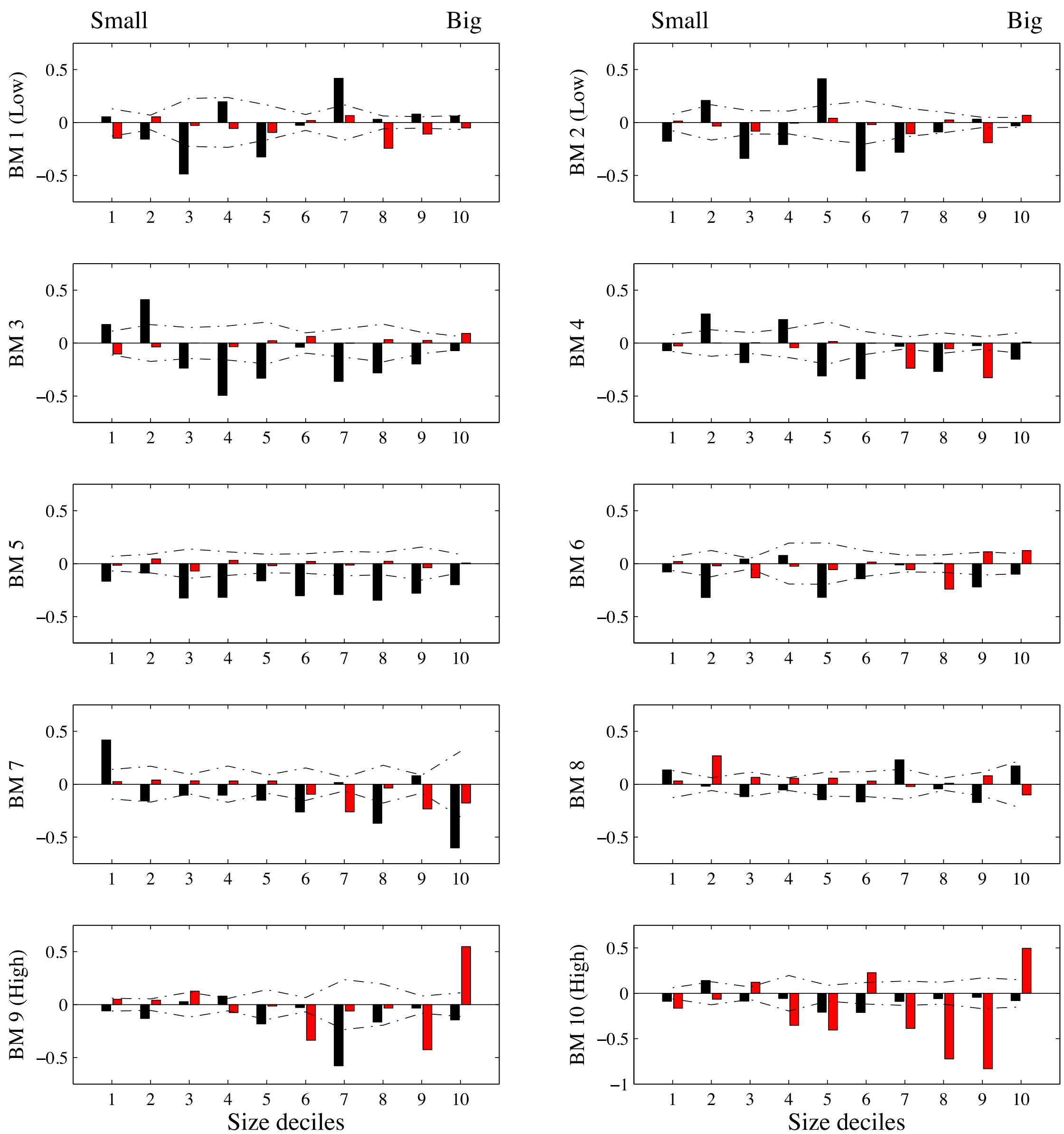

Fig. 4 Changes in the effect of momentum on the equity premium: The figure shows the coefficients associated to momentum in the extreme regimes of "low uncertainty", in black to the left, and "high uncertainty", in red to the right. The dotted line corresponds to 1.96 times the standard error of the momentum coefficient in the linear part of the model. That is, in the low uncertainty regime. Those estimates were obtained using 100 value-weighted portfolios sorted according to size and book to market factors. Our sample runs from Jan: 1985 to Nov: 2016. The linearity tests (which are not reported) indicate that roughly 43% (33%) of the portfolios present evidence against linearity in the momentum factor at 90% (95%) level of confidence.

4.4. Momentum betas for big caps (and other portfolios)

In this section we analyze changes in the momentum betas under different levels of economic uncertainty, using univariate sorts according to size, B/M, investment, and operating profitability. Our main results are shown in Figure 5, in which the betas were calculated using the five-factor Fama-French model. Similar conclusions can be extracted from the three-factor model and for this reason we do not to report them here. Linearity tests (that are not reported neither) indicate that roughly 57,5% of the portfolios present evidence of non-linearity in the momentum factor at 95% level of confidence, for the five-factor model.

Size exhibits a mixed set of results. While momentum factor clearly loses importance for the first six deciles (small stocks), it gains (negative) importance for the biggest four. This new result allows us to understand the puzzling behaviour of the medium-big portfolios (3^{rd} to 5^{th} quintiles of size) in the intersection with high momentum (5^{th} quintile of momentum) documented before, in section 4.1. We noticed then that momentum factor did no gain importance for these portfolios, in high uncertainty regimes, even when for most of the extreme quantiles of momentum the effect of high uncertainty on the momentum betas was reinforcing them. Comparing this with the results provided by the univariate sort of size, we realize that momentum and size orderings operate in opposite directions. That is, while high momentum portfolios experience an increase in their momentum betas under high uncertainty regimes, big portfolios experience a negative effect in their momentum betas under high uncertainty. As a consequence of this tension, big-high momentum firms do not fit the pattern documented for the other extreme quintiles in the 25 portfolios. Therefore, we conclude that for highly dependent on prior results quintiles the general trend is that *momentum increases under high uncertainty*. Only an even larger reduction following the size dimension may neutralize this effect, which is possible for the biggest portfolios.

Focusing on B/M portfolios we found a similar picture. First, momentum is either zero or negative in the low uncertainty regime, as is widely known and has been documented before using linear models. Second, the effects of momentum disappear in the high uncertainty regime, more or less from the 1^{st} to the 5^{th} decile. From the median-up the pattern is more erratic, sometimes the effect becomes more negative, equal to zero, or positive. Thus, the only conclusion in this case is that for low B/M stocks, momentum loses importance during episodes of high uncertainty.

According to investment and operating profitability the effects of momentum are likely insignificant, but when they are significant it is almost always in the low uncertainty regime. It seems as well that momentum is more important for conservative firms (high deciles in the investment sort) than it is for aggressive firms (lower deciles in the investment category). The panorama reverses for the stocks sorted in portfolios according to their operating profitability. In this case, momentum seems more relevant for low profitability stocks than it is for more profitable stocks.

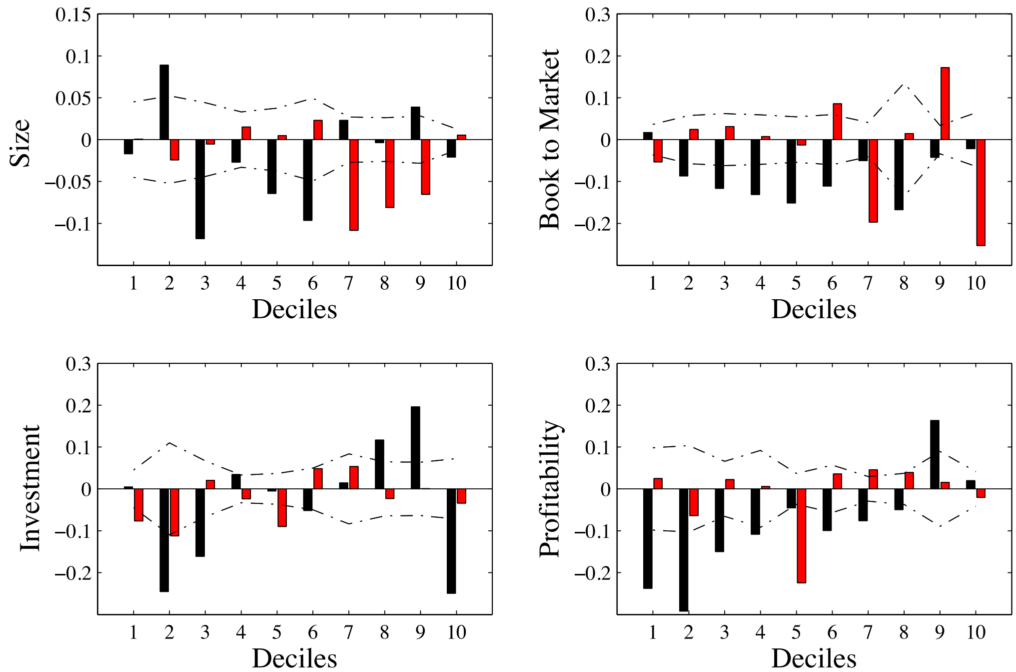

Fig. 5 Changes in the effect of momentum on the equity premium for portfolios constructed on univariate sorts: The figure shows the coefficients associated to momentum in the extreme regimes of low uncertainty, bars in black to the left, and high uncertainty, bars in red to the right. The dotted line corresponds to 1.96 times the standard error of the momentum coefficient in the linear part of the model (i.e. low uncertainty regime). Those estimates were obtained using four different samples of 10 value-weighted portfolios, each sorted according to one of the following criteria; size, book to market, investment and operating profitability. Our sample runs from Jan: 1985 to Nov: 2016. Linearity tests (that are not reported) indicate that roughly 55.0% (47.5%) of the portfolios present evidence of non-linearity in the momentum factor at 90% (95%) level of confidence.

4.5. Momentum moments and economic uncertainty

In this section we analyze how uncertainty regimes affect the momentum factor itself and its relation with the other systemic factors. Consider the estimates in equation 8:

$$MOM_t = \underset{(0.32)}{1.08} \underset{(0.06)}{-0.15(R_M - R_F)} \underset{(0.08)}{+0.10SMB_t} \underset{(0.11)}{-0.68HML_t} \underset{(0.11)}{+0.31RMW_t} \underset{(0.16)}{+0.56CMA_t} \underset{(0.44)}{-1.14d^u}, \tag{8}$$

where d^u is an indicator that is equal to 1 when uncertainty is high (above c^{*}=101.38), and 0 otherwise; standard errors in brackets. Thus, momentum has abnormal returns of 1.08% per month after controlling for its exposure to the Fama and French (2015) risk factors in the low uncertainty regime. Nevertheless, it has -0.06% (1.08 minus 1.14) in the high uncertainty regime. This amounts to a 13% per year abnormal return *if* uncertainty is low during such year, and to -0.72% *if* it is high. Moreover, not all the signs in front of the factor loads are negative, so momentum does not necessarily diversifies risk all the time.

To gain more insights about the evolving nature of momentum under different regimes of uncertainty, we have estimated descriptive statistics of the momentum factor for the full sample and for subsamples, constructed according to our estimates of the low and high uncertainty states. The differences are notorious. While the Sharpe ratio for the total period is 0.12 (despite of the uncertainty level), it is more than double for the low uncertainty regime (0.28), and almost *zero* for the high uncertainty regime (0.01). That is, the Sharpe ratio of the momentum strategy is 32.5 times larger in the high uncertainty regime than the Sharpe ratio in the low uncertainty regime. Additionally, skewness goes from positive (1.00) to negative (-2.16) when we change from low to high uncertainty, and (excess) kurtosis is considerably reduced as well, from 10.5 to roughly a half, 4.78.

Table 5. Descriptive statistics and Sharpe ratio of momentum under two uncertainty regimes: The regimes were separate according to the average threshold estimated using the five-factor model, which is 101.38.

	Maximum	Minimum	Mean	Standard deviation	Kurtosis	Skewness	Sharpe Ratio
Total Sample N=383	18.380	-34.580	0.538	4.621	11.727	-1.563	0.117
Low Uncertainty N=196	18.380	-9.080	1.013	3.645	4.778	1.003	0.278
High Uncertainty N=189	12.480	-34.580	0.046	5.419	10.504	-2.158	0.009

If we compare our results to the ones reported by Barroso and Santa-Clara (2015), we have that while their volatility-managed strategy gets an improvement in the Sharpe ratio by an order of 1.83 (from 0.53 in the unmanaged version of winners minus loser returns to 0.97 in the managed version), we have that here the is an improvement by a factor of 2.53 from a trading strategy that do not depend on uncertainty to a strategy that only trades momentum in low uncertainty regimes. Furthermore, we calculate an improvement in the Sharpe ratio by an order of 32.5, when we compared high with low uncertainty regimes. This does not eliminate the higher order risks (the other strategies in the literature neither do it), but it considerably reduces them in terms of kurtosis from 11.72 (total) and 10.50 (high) to 4.78 (low). Moreover, skewness risk vanishes with such a strategy, going from negative values in total (-1.56) and high uncertainty (-2.16) to a positive value in low uncertainty (1.00).

Of course here the crucial parameter is the uncertainty threshold c^*, which was estimated as the average of the threshold estimates in each of the 25 VW momentum-size portfolios as 101.38. We need to know *ex ante* this value in order to determine if we will be in a high or a low uncertainty regime next month. This parameter seems very stable (it is 102.57 for the three-factor model fitted on the same portfolios, 104.84 and 100.4 for the five- and three-factor models respectively, fitted on the 100 portfolios). Moreover the economic policy uncertainty index proposed by Baker et al. (2016) index is highly persistent[17]:

$$u_t = \underset{(3.30)}{18.91} + \underset{(0.03)}{0.86u_{t-1}}, \tag{9}$$

thus when the economic policy uncertainty index exceeds 95.9 in a certain month, we will recommend you better to abandon your momentum position. The strategy is, as in macroeconomics, *wait and see* until uncertainty is resolved (Bachmann and Bayer, 2013), or in this case, until it is low again.

5. Conclusions

We document a non-linear behavior of momentum when explaining the equity premium. This non-linearity is governed by the level of economic uncertainty prevailing in the economy. To this end, we used both Fama-French three and five-factor models. Our specifications consider market, size, B/M, profitability and investment as explanatory portfolios, on top of non-linear momentum. We show that, for most of the portfolios analyzed, which include portfolios sorted according to momentum and size, size and B/M, size only, B/M only, profitability and investment, momentum is a more relevant factor under regimes of low uncertainty than under high uncertainty. One exception to this behavior is portfolios largely dependent on prior returns, either negatively or positively (that is the 1st and 5th quintiles in the momentum sorts).

We conjecture that under high uncertainty episodes investors find it difficult to construct accurate estimates of what is going on in terms of momentum for each stock, as a pricing factor and, therefore, they prefer to follow strong trends that were present in the market before, under the low-uncertainty regime. If they do not feel that certain portfolio or stock has a particularly strong trend, they simple do not bet on momentum any more or at least they do it on a considerable smaller magnitude compared to the low uncertainty case.

These findings have obvious implications for asset pricing and portfolio allocation. In particular we explored *momentum moments* under the two regimes of uncertainty that we estimated. We found that indeed, even when the inclusion of the momentum factor in the set of regressors helps to attain smaller pricing errors, this strategy comes at an elevated cost. Indeed, the abnormal returns produced by momentum *disappear* during high uncertainty regimes in the market, its Sharpe ratio goes to *zero*, kurtosis of the momentum strategy *doubles* and skewness goes from *positive* to *negative.* Our simple recommendation is not to trade momentum when you expect uncertainty to be high. This can be done after forecasting economic uncertainty, which indeed is a very persistent process and then, using the threshold separating the uncertainty regimes, which is recorded here, to decide to quit or to stay.

As a final thought, we would like to note that the discussion above could be restated in a reverse order. From our presentation it seems that a change in the beta associated to the

[17] Unit root test are ambiguous. ERS rejects the presence of a unit root, while ADF does not and KPSS stays in the threshold rejection of the null, which in that case is stationarity, so better not to use equation 9 to forecast more than a couple of months ahead. This does not change the argument in the main text: uncertainty is persistent.

momentum factor on the excess returns (equation 2), is followed by a change in the unconditional distribution of momentum itself. Nevertheless, the situation could be just the opposite: a change in the probability distribution of momentum may induce a change in the beta associated to the momentum factor in the equity premium equation. If the latter is the case, our framework offers a unique opportunity to think of superexogenity in the three- and five-factor models, regarding momentum as a factor. Engle et al. (1983) introduced the concept of superexogeneity in the time series literature. It denotes a condition where a variable can be treated as given in a model in spite of a regime change in the process generating that variable. Therefore, in a relationship between two variables, say the equity premium and momentum, with a slope coefficient b^{MOM}, super exogeneity warranted the invariance of b^{MOM} to changes in the distribution of momentum. Favero and Hendry (1992) showed that changes in the coefficient associated to the RHS variable b are hard to detect if the RHS variable have a zero mean, as happens to be the case when the RHS are portfolio returns. By contrast, changes in b are easier to detect if the RHS variable had a nonzero mean. The mean of the LHS would then shift, relative to the past, involving a location shift. In this study we explored both: location shifts in the excess returns (changes in the intercepts) and changes in the momentum beta. We found that the latter are more relevant that the former, and also that they depend on uncertainty. This situation, as pointed out before, has key implications for pricing and trading in the stock market.

References

Andrews, D.W.K, and W. Ploberger. 1994. Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica* 62: 1383-1414.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. *Journal of Finance* 68:929–85.

Baker, S., N. Bloom, and D. Steven. 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics* 131:1593-1636.

Bali, T., and H. Zhou. 2016. Risk, uncertainty, and expected returns. *Journal of Financial and Quantitative Analysis* 51: 707-735.

Bachmann, R., and C. Bayer. 2013.'Wait-and-see' business cycles? *Journal of Monetary Economics* 60, 704: 719.

Barberis, N., Greenwood, R., L. Jin, and A. Shleifer. 2015. X-CAPM: An extrapolative capital asset pricing model. *Journal of Financial Economics* 115: 1-24.

Barroso, P., and P. Santa-Clara. 2015. Momentum has its moments. *Journal of Financial Economics* 116: 111-120.

Birru. J. 2015. Confusion of confusions: a test of disposition effect and momentum. *The Review of Financial Studies* 28:1849-1873.

Blitz, D., J. Huij, and M. Martens. 2011. Residual momentum. *Journal of Empirical Finance* 18: 506–521.

Boons, M. 2016. State variables, macroeconomic activity, and the cross section of individual stocks. *Journal of Financial Economics* 119: 489-511.

Branch, W., and G.W., Evans. 2011. Learning about risk and return: a simple model of bubbles and crashes. *American Economic Journal: Macroeconomics* 3:159-191.

Brogaard, J., and A. Detzel. 2015. The asset-pricing implications of government economic policy uncertainty. *Management Science* 61:3-18.

Campbell, R.H., Y. Liu, and H. Zhu. 2016. … and the cross-section of expected returns. *The Review of*

Financial Studies 29:5-68.

Carhart, M.M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57:82.

Chow, G.C. 1960. Tests of equality between sets of coefficients in two linear regressions. *Econometrica* 52: 211-22.

Chui, A., S. Titman, and K.C.J. Wei. 2010, Individualism and momentum around the world, *Journal of Finance* 65, 361:392.

Chuliá, H., Gupta, R., J.M. Uribe, and M. Wohar. 2017a. Impact of us uncertainties on emerging and mature markets: evidence from a quantile-vector autoregressive approach. Journal of International Financial Markets, Institutions & Money. In press. Doi: dx.doi.org/10.1016/j.intfin.2016.12.003

Chuliá, H., M. Guillén, and J.M. Uribe. 2017b. Measuring uncertainty in the stock market. *International Review of Economics and Finance* 48: 18-33.

Cochrane, J. 2005. *Asset pricing* (Revised ed.). New Jersey: Princeton University Press.

Cooper, M.J., R. Gutierrez, and A. Hameed. 2004, Market states and momentum. *The Journal of Finance* 59:1345-1365.

Daniel, K., and T.J. Moskowitz. 2016. Momentum crashes. *Journal of Financial Economics* 122: 221-247.

Daniel, K., and S. Titman. 2006. Market reaction to tangible and intangible information. *Journal of Finance* 61:1605–43.

Daniel, K., D., Hirshleifer, and A. Subrahmanyam.1998. Investor psychology and security market under- and overreactions. *Journal of Finance* 53, 1839:1885.

Engle, R., D. F. Hendry, and J.F. Richard. 1983. Exogeneity. *Econometrica* 51, 277: 304.

Evans, G.W, and S., Honkapohka. 2001. *Learning and expectations in macroeconomics*. New Jersey: Princeton University Press.

Fama, E., and K. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33: 3–56.

Fama, E., and K. French. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116: 1-22.

Fama, E., and K. French. 2016. Dissecting anomalies with a five-factor model. *The Review of Financial Studies* 29:69-103.

Favero, C., and D. F. Hendry. 1992. Testing the Lucas critique: A review. *Econometric Reviews* 11, 265:306.

Fernandes, M., M. C. Medeiros, and M. Scharth. 2014. Modeling and predicting the cboe market volatility index. *Journal of Banking and Finance* 40:1-10.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident. *Review of Financial Studies* 14: 1-27.

Grundy, B., Martin, J., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies* 14: 29-78.

Hansen, B.E. 1992a. Testing for parameter instability in linear models. *Journal of Policy Modeling* 14(4): 517-533.

Hansen, B.E. 1992b. Tests for parameter instability in regressions with I(1) processes. *Journal of Business and Economic Statistics* 10: 321-336.

Hillebrand, E., and M. C. Medeiros, and J. Xu. 2013. Asymptotic theory for regressions with smoothly changing parameters. *Journal of Time Series Econometrics* 5, 133-162.

Hillebrand, E., and M.C. Medeiros. 2016. Nonlinearity, breaks, and long-range dependence in time series models. *Journal of Business & Economic Statistics* 34:23-41.

Hiller, A., H Jacobs, and S. Muller. 2014. Media makes momentum. *The Review of Financial Studies* 27: 3467-3501.

Hong, H., and J. Stein. 1999. A unified theory of under reaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54, 2143:2184.

Jagannathan, R., and Z. Wang. 1996. The conditional CAPM and the cross- section of expected returns. *Journal of Finance* 51: 3–53.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance* 48:65–91.

Johnson, T., 2002. Rational momentum effects. *Journal of Finance* 57, 585:608.

Jurado, K., S.C., Ludvigson, and S. Ng, 2015. Measuring uncertainty. *American Economic Review* 105: 1177-1216.

Knight, F. 1921. *Risk, uncertainty, and profit*. Boston: Hart, Schaffner & Marx; Houghton Mifflin Co.

Lettau, M., and S. Ludvigson. 2001. Resurrecting the (C) CAPM: a cross- sectional test when risk premia are time-varying. *Journal of Political Economy* 109: 1238–1287.

Liu, L.X., and L. Zhang. 2008. Momentum profits, factor pricing, and macroeconomic risk. *The Review of Financial Studies* 21: 2417-2448.

Maio, P., and P. Santa-Clara. 2012. Multifactor models and their consistency with the ICAPM. *Journal of Financial Economics* 106: 586-613.

McAleer, M., and M.C. Medeiros. 2008. A Multiple regime smooth transition heterogeneous autoregressive model for long memory and asymmetries. *Journal of Econometrics* 147: 104-119.

Moskowitz, T.J., Y.H., Ooi, and Pedersen, L.H. 2012. Time series momentum. *Journal of Financial Economics* 104: 228-250.

Novy-Marx, R. 2012. Is momentum really momentum. *Journal of Financial Economics* 103: 429-453.

Nyblom, J. 1989. Testing for the constancy of parameters over time. *Journal of the American Statistical Association* 84 (405): 223-230.

Sagi, J., and M. Seasholes. 2007. Firm-specific attributes and the cross section of momentum. *Journal of Financial Economics* 84, 389:434.

Savor, P., and M. Wilson. 2014. Asset pricing: A tale of two days. *Journal of Financial Economics* 113: 171-201.

Segal, G., I. Shaliastovich, and A. Yaron. 2015. Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics* 117: 369-397.

Zeileis, A. 2005. A unified approach to structural change tests based on ML scores, F statistics, and OLS residuals. *Econometric Reviews* 24(4): 445–466.

Zeileis, A. 2006. Implementing a class of structural change tests: an econometric computing approach. *Computational Statistics & Data Analysis* 50: 2987-3008.

Appendix

Table A1. Gamma and c estimates: The table shows the summary statistics for the estimates of the logistic parameter, , that is called the slope parameter and determines the s*peed of the transition between two limiting regimes*. When the parameter $\gamma \rightarrow \infty$, the logistic function becomes a step function, and the STR model becomes a threshold specification. Parameter $c*$ serves as a threshold to separate the two regimes depending on the uncertainty variable realizations.

Panel A: Five Factor Model

Parameter	γ	$c*$
Mean	99.807	101.379
Max	547.570	142.990
Min	9.999	84.559
Stad. Dev.	143.685	21.727

Panel B: Three Factor Model

Parameter	γ	$c*$
Mean	67.116	102.369
Max	405.520	143.820
Min	4.927	73.427
Stad. Dev.	92.561	24.532

Table A2. Linear estimates of the model: The table shows the linear estimates of the coefficients of the 5-factor model and the 3-factor model.

Mom	Low	2	3	4	High	Mom	Low	2	3	4	High
Panel A: Five Factor Model						*Panel B: Three Factor Model*					
			b						b		
Small	1.00	0.88	0.87	0.86	1.01	Small	1.06	0.87	0.85	0.85	1.04
2	1.18	1.01	0.96	0.96	1.13	2	1.21	0.99	0.93	0.94	1.16
3	1.16	1.04	0.97	1.02	1.14	3	1.19	1.01	0.94	0.99	1.15
4	1.16	1.11	1.02	1.02	1.09	4	1.19	1.05	0.98	0.98	1.10
Big	1.10	0.95	0.95	0.98	1.07	Big	1.12	0.91	0.93	0.94	1.08
			s						s		
Small	1.07	0.93	0.83	0.86	1.04	Small	1.14	0.91	0.80	0.87	1.12
2	0.95	0.90	0.79	0.84	0.98	2	0.99	0.83	0.71	0.79	1.02
3	0.58	0.55	0.57	0.57	0.74	3	0.63	0.46	0.48	0.48	0.74
4	0.26	0.25	0.26	0.23	0.45	4	0.30	0.19	0.16	0.14	0.46
Big	-0.11	-0.14	-0.13	-0.18	-0.09	Big	-0.12	-0.19	-0.17	-0.22	-0.09
			h						h		
Small	0.08	0.27	0.30	0.24	0.11	Small	-0.02	0.32	0.35	0.27	0.04
2	0.02	0.20	0.24	0.20	0.03	2	-0.07	0.24	0.28	0.22	-0.08
3	-0.01	0.17	0.24	0.28	-0.02	3	-0.11	0.21	0.29	0.32	-0.08
4	0.02	0.08	0.19	0.14	-0.02	4	-0.04	0.24	0.28	0.24	-0.04
Big	0.05	0.09	0.13	0.07	-0.01	Big	-0.01	0.18	0.17	0.18	-0.06
			r								
Small	-0.39	0.07	0.11	-0.01	-0.28						
2	-0.14	0.24	0.27	0.16	-0.16						
3	-0.17	0.30	0.34	0.31	0.00						
4	-0.13	0.36	0.33	0.31	-0.05						
Big	0.01	0.19	0.17	0.18	0.00						
			c								
Small	-0.10	0.08	0.08	0.08	0.00						
2	-0.11	-0.01	-0.02	-0.02	-0.18						
3	-0.14	-0.04	0.00	-0.03	-0.13						
4	-0.07	0.23	0.08	0.08	-0.02						
Big	-0.14	0.10	0.02	0.17	-0.10						

Table A3. t-statistics associated to linear estimates of the model: The table shows the t-statistics associated to the linear estimates of the coefficients of the 5-factor model and the 3-factor model.

Panel A: Five Factor Model

Mom	Low	2	3	4	High
			t(b)		
Small	30,04	42,61	43,96	41,23	36,78
2	52,71	54,37	53,05	56,00	57,25
3	38,40	53,44	53,46	52,07	55,93
4	35,18	53,84	54,82	53,56	46,71
Big	30,29	45,26	54,27	56,15	53,84
			t(s)		
Small	22,40	31,23	29,23	28,87	26,46
2	29,59	33,67	30,59	33,67	34,93
3	13,48	19,57	21,86	20,15	25,30
4	5,55	8,35	9,45	8,49	13,40
Big	-2,13	-4,57	-4,98	-7,13	-3,00
			t(h)		
Small	1,24	6,73	7,79	5,94	2,02
2	0,39	5,47	6,81	5,95	0,88
3	-0,16	4,66	6,92	7,32	-0,51
4	0,34	1,91	5,13	3,87	-0,44
Big	0,74	2,34	3,98	2,07	-0,28
			t(r)		
Small	-6,28	1,95	3,04	-0,30	-5,41
2	-3,27	6,68	7,81	5,04	-4,09
3	-2,98	7,87	9,82	8,18	-0,10
4	-2,15	9,33	9,27	8,53	-1,25
Big	0,18	4,81	4,91	5,22	0,03
			t(c*)		
Small	-1,06	1,38	1,53	1,36	-0,05
2	-1,80	-0,29	-0,34	-0,49	-3,27
3	-1,70	-0,84	-0,08	-0,48	-2,27
4	-0,81	4,10	1,53	1,47	-0,33
Big	-1,35	1,72	0,40	3,61	-1,92

Panel B: Three Factor Model

Mom	Low	2	3	4	High
			t(b)		
Small	32,89	44,83	45,93	44,23	37,59
2	57,38	54,10	51,53	57,66	62,02
3	42,27	51,91	50,50	49,77	60,98
4	38,63	50,88	51,68	50,90	50,70
Big	32,97	45,94	55,67	55,74	58,63
			t(s)		
Small	24,20	33,24	30,17	31,50	29,92
2	32,87	31,83	27,59	32,96	38,08
3	15,51	16,44	18,02	16,93	27,11
4	6,81	6,28	5,85	5,28	15,13
Big	-2,58	-6,80	-7,17	-9,06	-3,51
			t(h)		
Small	-0,38	11,05	12,43	9,29	0,98
2	-2,06	8,48	10,23	8,68	-2,66
3	-2,50	7,11	10,44	10,69	-2,85
4	-0,90	7,79	9,81	8,25	-1,32
Big	-0,11	6,00	6,84	6,99	-2,07