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Uncertainty-Risk and the Cross-Section of Expected Returns

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"Data! Data! Data! I can't make bricks without clay."

Sherlock Holmes, The Adventure of the Copper Beeches

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Abstract

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Uncertainty-Risk and the Cross-Section of Expected Returns

by Julian TERSTEGGE

I examine the pricing of uncertainty-risk in the cross-section of stock returns. Several theoretical channels can be used to argue why investors should be willing to accept lower expected returns on stocks with a high exposure to innovations in uncertainty. I replicate the seminal paper of Ang et al. (2006), who use the VXO implied volatility index as a proxy for uncertainty and confirm their results that, consistent with these theories, there is a significant negative relationship between stocks' covariance with the VXO and their average returns over the period of 1986 to 2000. Subsequently, I update their study to 1986 to 2018 and find a similar, though weakened, relationship. I show the empirical support for an uncertainty-risk factor to have steadily increased until the early 2000s and steadily decreased since then. Finally, I examine the TYVIX implied treasury volatility index among post-crisis US banking stocks and find higher average returns for stocks that covary positively with this index. This reversed price of uncertainty-risk is consistent with government guarantees against interest-rate-uncertainty induced bank defaults.

Contents

List of Figures

List of Tables

List of Abbreviations

MKT	Return on the **Mark**e**t** Portfolio, in excess of the risk-free rate
SMB	Return of the Fama and French (1993) **S**mall **M**inus **B**ig Portfolio
HML	Return of the Fama and French (1993) **H**igh **M**inus **L**ow Portfolio
CMA	Return of the Fama and French (2015) **C**onservative **M**inus **A**ggressive Portfolio
RMW	Return of the Fama and French (2015) **R**obust **M**inus **W**eak Portfolio
AHXZ	Ang et al. (2006) by **A**ng, **H**odrick, **X**ing and **Z**hang
FVXO	Return of the Ang et al. (2006) **F**actor, mimicking the first-difference of the **VXO** implied volatility index
FTYVIX	Return of the Ang et al. (2006) **F**actor, mimicking the first-difference of the **TYVIX** implied treasury volatility index

Chapter 1

Introduction

Which stocks on average earn higher returns than others?

Perhaps no other question of finance is asked so often by lay investors, professional investors and researchers. The last of those three groups has produced a huge amount of theoretical, but especially empirical, research on the question which stocks on average earn significantly higher returns. Such studies usually take the form of *linear factor models*, where a stock's expected return in excess of the risk-free rate is given as a linear function of its return covariance with some variables. These variables are referred to as *risk factors*. This thesis investigates the question whether *uncertainty* should be included as one such risk factor.

Risk factor variables are supposed to explain why assets (I focus on equities) have different average returns, that is they are supposed to explain *the cross-section of expected returns*. The problem for research and practice alike lies in the abundance of factors that have been reported as being significant, but do not work out-of-sample after their publication. To alleviate this flood of useless factors, researchers demand economic reasoning behind a proposed cross-sectional risk factor, in addition to significant empirical performance.

In this respect, *uncertainty* is arguably one of the most promising candidates as a risk-factor, as it can be motivated theoretically through several channels. The most prominent channel is Merton (1973)'s Intertemporal Asset Pricing Model. The ICAPM implies that investors want to hedge against a deterioration of their *investment opportunities* and it can be argued both theoretically and empirically that an increase in uncertainty constitutes such a deterioration. Therefore, investors should be willing to pay a higher price (accept a lower expected return) on stocks that tend to have high returns when uncertainty increases, as those stocks function as hedges.

Ang et al. (2006) use the VXO implied volatility index as a proxy for uncertainty and find, in accordance with the ICAPM, significantly lower average returns for stocks that covaried positively with changes in the VXO over the period of 1986 to 2000.

To answer the question whether uncertainty risk is priced in the cross-section of stock returns this thesis replicates the relevant parts of their paper and subsequently updates them to the period of 1986 to 2018. Replication has the double function of making sure their results can be replicated (i.e. are not due to a faulty implementation on their part) and preventing implementation errors on my part, as a serious factor-analysis consist of numerous inconspicuous steps where junior researchers might make mistakes with far reaching consequences for the validity of results. Also, the discussion of evidence at two separate points in time allows for a view on factor-risk that is rare in the literature: the development of empirical evidence over time. Thus, trends in the empirical support for an uncertainty-risk factor become evident and a conjecture about the results of future studies can be given.

Moreover, Ang et al. (2006) use the VXO implied volatility index as their proxy for uncertainty, while there is nothing inherent in the theoretical justification of an uncertainty-risk factor that would mark VXO as its optimal proxy. Therefore, this thesis provides a new perspective on uncertainty-risk by changing the proxy to the TYVIX implied treasury volatility index. In particular, I test this index on the subset of US banking stocks over the sample of 2009 to 2018. My hypothesis is to find uncertainty-risk priced differently among these stocks, since the US government has shown its willingness to save large financial institutions in case of trouble. This hypothesis is motivated by Gandhi and Lustig (2015) who uncovered a new *size* risk-factor among post-crisis US bank stocks.

The rest of this thesis is organized as follows. Chapter 2 introduces the theory of factor models. Chapter 3 links the cross-sectional nature of factor models to time-series tests. In particular, the choice of factors as traded portfolios is motivated. Chapter 4 partially surveys the literature on pricing factors. This includes the presentation of risk-factors that are used for robustness tests in the empirical chapters, an introduction to the theory behind uncertainty-risk and a partial survey of the literature on uncertainty-risk factors. Chapter 5 explains the methodology of Ang et al. (2006) in detail, presents the results of my replication, presents the results of updating their study to 1986 to 2018 and discusses the development of evidence for a priced uncertainty-risk factor over time. Chapter 6 applies the Ang et al. (2006) procedure to the TYVIX index among post-crisis US banking stocks. Chapter 7 concludes.[1]

[1] Thus, chapters 2 to 4 provide an introduction and survey, while the empirical chapters 5 and 6 explain the methodology and results in detail. I have chosen this structure, as a master-thesis must

explain what could be assumed to be obvious in a paper. Such long deviations while explaining the methodology cannot fail to annoy the reader. Therefore, I isolated them into the early chapters and refer back where necessary.

Chapter 2

The Theory of Factor Models

Asset pricing tries to value uncertain future cash flow streams, taking the form of assets or liabilities. A minimum requirement for an asset pricing model is that it prices all possible streams consistently. That is, researchers are looking for one framework to price all stocks, bonds, derivatives and so on. One such framework are pricing factors.[1]

This chapter shortly introduces the theory of factor models generally, independent of any particular application. Emphasis is put on a selection of theorems that theoretically justify common empirical approaches. Unless stated otherwise, this whole chapter is based on Munk (2013).

The concept of factor models can be applied in discrete and continuous time. For explanatory purposes, a one period-economy is sufficient. A one-period economy consists of two discrete points in time $t = 0$ and $t = 1$.

Munk defines pricing factors the following way (Munk (2013), p.372): "In a one-period framework, a pricing factor is a random variable $\mathbf{x} = (x_1, ..., x_K)^T$ of some dimension K so that (i) the variance-covariance matrix $Var[\mathbf{x}]$ is non-singular and (ii) constants $\alpha \in \mathbb{R}$ and $\boldsymbol{\eta} \in \mathbb{R}^K$ exist so that

$$E[R_i] = \alpha + \boldsymbol{\beta}(R_i, \mathbf{x})^T \boldsymbol{\eta} \qquad i = 1, 2, .., I \tag{2.1}$$

where the factor-beta of asset i is the K-dimensional vector $\boldsymbol{\beta}(R_i, \mathbf{x})$ given by

$$\boldsymbol{\beta}(R_i, \mathbf{x}) = \frac{Cov(\boldsymbol{x}, R_i)}{Var(\boldsymbol{x})}." \tag{2.2}$$

Accordingly, a pricing factor is a random variable $\mathbf{x}$ of some dimension K whose beta with the return of each of the I assets in the market multiplied with some K dimensional η and added to a general α describes the respective asset's expected

[1] Others are for example Risk-Neutral Probabilities or Stochastic Discount Factors. Which framework is most appropriate depends on the application. Equities are mostly priced via factor models.

returns. α gives the expected return on an asset with $\boldsymbol{\beta} = 0$. If the risk-free asset is traded α, is its return. Generally, bold letters are used to denote matrices. Importantly, this is an expected return relationship and realized returns can deviate substantially. As discussed below and in later chapters, **x** should reflect a *risk* that investors want to avoid. This risk does not necessarily need to show up in investors' utility functions, but might come up during the derivation of equilibrium investment decisions (see for example Merton (1973)). $\boldsymbol{\beta}$ is asset specific and measures asset i's exposure to risk $\boldsymbol{x}$. Its empirical estimation is discussed in chapter 3 and executed numerous times throughout this thesis. In contrast, $\boldsymbol{\eta}$ is risk-specific. It measures to what extend investors want to be compensated for bearing risk $\boldsymbol{x}$. Therefore, $\boldsymbol{\eta}$ is called *factor risk premium*. Its empirical estimation is mentioned in chapter 3, but not followed up in detail in this thesis. I investigate the sign of $\boldsymbol{\eta}$ on uncertainty-risk but do not estimate its precise value.

If a factor is constructed such that it tends to change positively when the risk increases, investors should be willing to pay a higher price (accept a lower expected return) on stocks that are more exposed to the risk (i.e. that have a relatively high $\boldsymbol{\beta}$). If an investor's portfolio is skewed towards such stocks, he/she tends to earn relatively higher (lower) returns in states of the future where increases in the risk put her/him worse (better). Thus, the investor has reduced risk. The stocks have functioned as an *intertemporal hedge*. Such factors should carry a negative $\boldsymbol{\eta}$, which can easily be seen from equation 2.1 If a factor is constructed such that it tends to change positively when the risk decreases, the opposite argumentation applies. In particular, $\boldsymbol{\eta}$ is positive.

So far I have discussed K dimensional factors, factor exposures and factor-risk premia. This is not the form typically found in the literature. Usually, factor models are expressed like

$$E[R_i] = \alpha + \beta_{i1}(R_i, x_1)\eta_1 + \beta_{i2}(R_i, x_2)\eta_2 + ... + \beta_{iK}(R_i, x_K)\eta_K \qquad i = 1, 2, .., I \quad (2.3)$$

where one would typically write about K different factors $x_1, x_2, .., x_K$ and K different factor risk premia $\eta_1, \eta_2, ..., \eta_K$.

Equations 2.3 and 2.1 are equivalent if the elements of **x** in 2.1 are independent (see Munk (2013) p.373 for a formal prove). That is, all elements of **x** capture a risk that investors care about, but those aspects of risk do not covary. Testing risk-factors for orthogonality will be part of chapters 5 and 6.

However, Munk also shows that from any pricing factor an equally valid pricing factor can be constructed that is orthogonal to the first one (see Munk (2013) p.375

for a formal prove). Therefore, while orthogonality of factors is important for the validity of the functional form 2.3 and for the estimation of stocks' exposure to these factors (see chapter 3), no factor must be discarded because it correlates with other factors. Instead, it is always possible to *orthogonalize* a factor.

Chapter 3 derives why factors are commonly chosen to be the returns of traded portfolios. This might seem quite restrictive. Yet, for both K- dimensional factors $\mathbf{x}$ and one-dimensional factors x_1 Munk shows that the *factor-mimicking portfolio*, which is constructed such that the variance of the difference between its returns and changes in the factor is minimized, will also work as a pricing factor (see Munk (2013) p.376 and p.140, respectively). Thus, since for any factor there can always be found a factor-mimicking portfolio, the requirement for factors to be returns is not restrictive.

Finally, the problem of hundreds of factors being reported as significant but largely failing out-of-sample after their publication (see Harvey, Liu, and Zhu (2016) for a comprehensive study) can and should be addressed theoretically. Munk shows that "A return R^{mv} is a pricing factor, (...) if and only if R^{mv} is a mean-variance efficient return different from the minimum-variance return." (Munk (2013), p.392). This theorem implies that ex-post it is always possible to find any number of factors that seem to explain the cross-sectional dispersion in average returns. Yet, if these factors have no economic meaning but are just some *mean-variance efficient return different from the minimum-variance return*, they are unlikely to stay mean-variance efficient and thus unlikely to work as factors out-of-sample. This is why studies on empirical asset pricing (this thesis among them) are not exercises in pure statistics, trying to uncover the optimal past factor, but require a significant portion of theoretical argumentation to convince the profession of a factor's future potential.

Chapter 3

Estimating and Testing Linear Factor Models

After introducing the theory of linear factor models in chapter 2 and before discussing empirical studies in chapter 4, this chapter introduces general methods to estimate and test these models.

Due to the large empirical literature on linear pricing factors, there is also a large literature on methods to estimate and test them. Goyal (2012) divides these methods broadly into *time-series regressions* and *cross-sectional regressions*. Both are outlined below. The former are explained as they will find frequent application in later parts of the thesis. Especially, it is shown why I will interpret the intercepts of time-series regressions as *pricing errors*. Cross-sectional regressions are explained to motivate the construction of factors as traded portfolios, which will require some effort in chapters 5 and 6. The specific approaches applied in the empirical part of this thesis are described in these later chapters.

For simplicity, I will assume the risk-free asset is traded throughout this chapter. Also, I assume a return equation like 2.3 with $K = 1$ and constant factor risk exposures (β) and factor risk premia (η). That is, I assume to be testing a model of the form

$$E[R_i - R_f] = \beta_i(R_i, x)\eta \qquad i = 1, 2, .., I \tag{3.1}$$

, where R_i is the return of asset i,f denotes the risk-free asset, $\beta_i(R_i, x_1) = \frac{Cov(x,R_i)}{Var(x)}$ and x is some single pricing factor. According to equation 3.1 the expected excess return over the risk-free rate for all I assets is given by the beta of its returns with the pricing factor x multiplied by a general risk-premium.

3.1 Time-Series Approach

If the factor x is the return on a traded portfolio, α in regression 3.2 can be interpreted as the *pricing error* of model 3.1 with respect to asset i (Goyal (2012)). This is explained below.

In the time-series regression

$$R_t - R_f = \alpha + b(x_t - R_f) + \epsilon_t \qquad t = 1, 2, .., T \tag{3.2}$$

R_t is the return of some asset i over period t, R_f is assumed constant, α is the model's intercept, b the slope coefficient and ϵ_t is an error term. The Ordinary Least Squares (OLS) procedure estimates b as

$$\hat{b} = \frac{Cov(R - R_f, x - R_f)}{Var(x - R_f)} = \frac{Cov(R, x)}{Var(x)} \tag{3.3}$$

, where the hat indicates an OLS estimate and the second equality sign holds since I assumed a constant risk-free rate. Thus, the estimate of the slope coefficient from regression 3.2 is the asset's exposure to the risk factor x given as β_i in equation 3.1.

At this point it is crucial that the factor x is the return on a traded portfolio. Only under this condition must the factor itself be priced by the model, that is it can be put on the left side of the regression 3.2:

$$x_t - R_f = \alpha + b(x_t - R_f) + \epsilon_t \qquad t = 1, 2, .., T \tag{3.4}$$

Regressing a variable on itself necessarily results in an $\hat{\alpha}$ of zero and a $\hat{b}$ of one. By nature of OLS, taking the unconditional mean (or unconditional expectation $E[\ ]$) of 3.4 results in:

$$E[x_t - R_f] = \hat{\alpha} + \hat{b}E[x_t - R_f] \tag{3.5}$$

From 3.4 it is known that $\hat{\alpha} = 0$ and $\hat{b} = 1$. Therefore, a comparison with the pricing model 3.1 applied to the factor x:

$$E[x_t - R_f] = \alpha + \beta_i \eta \tag{3.6}$$

and the knowledge from above that $\hat{b} = \beta_i$, shows that a factor's unconditional mean minus the risk-free rate is equal to its risk premium η. This derivation is not valid for non-traded factors, as their changes are not returns and thus cannot be put on the left side of 3.2

Take the unconditional expectation of 3.2 for any asset:

$$E[R_t - R_f] = \hat{\alpha} + \hat{b}E[x_t - R_f] \tag{3.7}$$

with the knowledge that $E[x_t - R_f] = \eta$ and $\hat{b} = \beta_i$ and a comparison with the model 3.1 shows that if model 3.1 is correct, $\hat{\alpha}$ will be zero. That is, if all variation in expected returns is explained by exposure to the risk factor x, all alphas in the time-series regression 3.2 can be interpreted as *pricing errors*. This links the cross-sectional nature of the asset pricing models to time-series tests.

In chapter 5, I use this method of generating pricing errors to test the robustness of my results against the inclusion of other possible risk-factors. Such time-series tests of factor models are commonly executed for several assets simultaneously.[1] When several assets are available, the model is concluded to not completely explain returns if the hypothesis that all alphas are jointly zero can be rejected. I employ the standard F-test of Gibbons, Ross, and Shanken (1989) for this purpose.

Finally, it should be noted that time series regressions frequently exhibit heteroskedasticity and autocorrelation in errors ϵ_t, thus violating the OLS assumptions. This is usually solved via the Newey and West (1987) correction of standard errors (Goyal (2012)).

3.2 Cross-Sectional Approach

If the factor considered is not the return on a traded portfolio, there is no reason to assume that the risk premium η is equal to the factor mean minus the risk-free rate $E[x_t - R_f]$. Therefore, the α from regression 3.2 must not be zero for the model 3.1 to be correct. As a result, the time-series approach described above is not viable if the factor is not a traded asset.

Instead, researchers usually test the more direct implication of the asset pricing model, that the I β_i explain the dispersion in average returns of the I assets. This is also the preferred approach when a large number of assets is considered simultaneously (Goyal (2012)).

To that end, first the time-series regression 3.2 is estimated for each asset i. Subsequently, the resulting I $\hat{b}$s are used on the right side of the single cross-sectional regression

$$\bar{R}_T = \alpha + B\gamma + \epsilon_i, \tag{3.8}$$

[1] Usually these assets are portfolios to obtain balanced panels (i.e. returns for all t's and all assets). Chapter 5 discusses this in detail.

where $\bar{R}_T$ is the vector of average returns from $t = 1$ to $t = T$ of the I assets, B is the vector of $\hat{b}$s from the preparatory time-series regressions, α is the intercept, γ the slope coefficient and ϵ_i is the error term.

Such a procedure is called a *two-pass regression*. The estimated $\hat{\gamma}$ has the interpretation of a *factor risk premium*. That is, it gives the η in equation 3.1(Goyal (2012)). The intercept α in from regression 3.8 captures the average expected return across assets that is not explained by factor risk exposure, i.e. the return to be expected when the factor exposure $\hat{B}$ is zero.[2] The *pricing error* lies in the residuals ϵ_i, since they capture all the variation in average returns that can neither be explained by factor risk exposure, nor by the zero-factor-risk return α. This short introduction to cross-sectional estimation approaches shall suffice to motivate the construction of factors as traded portfolios in order to be able to use time-series regressions and obtain pricing errors via intercepts.

It should only be noted that, if the factor is a traded portfolio, time-series regressions and cross-sectional regressions are complementary (Goyal (2012)). The time-series approach tests the model implication that alphas should be zero, while the cross-sectional approach tests that betas should explain differences in average returns across assets. Both are equally valid model implications and could lead to a model rejection. For further information on the similarities and differences between cross-sectional and time-series tests of linear factor models see Goyal and Jegadeesh (2017).

[2] α is also the expected return implied by the model if the factor risk premium γ is zero. However, a model with zero factor risk-premium would not explain anything. Therefore, this is not a valid case.

Chapter 4

Risk-Factors and the Cross-Section of Expected Returns

The abundance of empirical literature on seemingly significant linear pricing factors is nicely summarized in the title of Harvey, Liu, and Zhu (2016): "... and the Cross-Section of Expected Returns". In this chapter, I survey the literature on pricing factors, but limit myself to those parts that are relevant for chapters 5 and 6, where I conduct my own empirical analysis.

According to Goyal (2012), on whose excellent survey much of the first three sections of this chapter is based, there are generally three ways to motivate pricing factors: theoretically (see section 4.1), statistically (see section 4.2) and based on firm characteristics (see section 4.3). A central point arising from this survey is the special position of the uncertainty factor as one of the few that can be motivated theoretically. Section 4.4 provides some examples of variables that have been used as proxies for uncertainty, in particular the VXO and TYVIX implied volatility indices. The section also gives a short overview of previous empirical work on the uncertainty-risk factor.

Thus, this chapter provides theoretical foundations for an uncertainty-risk factor, puts uncertainty-risk into perspective to other factors, discusses variables that can be used as observable proxies for uncertainty and introduces variables whose cross-sectional effect has to be controlled for when examining uncertainty-risk in chapters 5 and 6.

4.1 Theoretically Motivated Factors

As a first significant theory, the Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM is a single-period (i.e. static) equilibrium model. It assumes homogeneous expectations and shows that, if investors choose their portfolios according to the Markowitz (1952) mean-variance criterion, *market risk* is the only risk that cannot be diversified away (i.e. the only systematic risk factor). Using the theory of chapter two, the CAPM implies the return of the market portfolio as the only x_i in equation 2.3. In other words, the CAPM predicts stocks' returns in excess of the risk-free rate to be proportional to their covariance with the return of the market portfolio. In the following, I will frequently refer to the market portfolio's return as *the market factor*, or *MKT*.

Serious empirical objections have been raised against the CAPM as early as Black, Jensen, and Scholes (1972), who most notably found that the US security market line is flatter than predicted by the CAPM (i.e. low (high) market-beta stocks tend to earn higher (lower) returns than predicted) (Goyal (2012)). Maybe due to its simplicity, the CAPM is still the first pricing model to beat when a new factor is suggested. Therefore, I control for MKT at every stage of the following two chapters.

Since the CAPM is a static model, it holds intertemporally only if preferences and expected stock returns are not state-dependent (Fama (1970)). That is, they do not change over time whatever state of the world is realized. However, a lot of time-series evidence suggests that expected stock returns are not constant over time (see for example Fama and French (1989)). This is why Merton (1973) developed the Intertemporal Capital Asset Pricing Model (ICAPM). The ICAPM holds intertemporally without the assumption of state-independent preferences and expected stock returns. Merton refers to *the expectation of future stock returns* as the *investment opportunity set* or simply *investment opportunities*. The model is still based on homogeneous expectations and investors maximizing the expected value of their lifetime consumption. In contrast to the CAPM, Merton derives a multifactor model of expected returns where additional risk factors can consist of any state-variable that describes the time-variation of investment opportunities. It should be noted that the term *investment opportunities* describes the expected value of future stock returns. Thus, investment opportunities can vary with either news about future cash flows or discount rates. That is, if a variable describes either future cash flows or discount rates it is a potential x_i in equation 2.3 of Merton's ICAPM (Goyal (2012)).

Various candidates have been proposed. Among others, macroeconomic variables like inflation or industrial production growth (Chen, Roll, and Ross (1986)) investors' marginal utility of consumption (Breeden (1979)) , the aggregate consumption-wealth ratio (Lettau and Ludvigson (2001a) and Lettau and Ludvigson (2001b)) and market-wide uncertainty (see section 4.4). Thus, Merton (1973)'s ICAPM is sufficient to motivate the inclusion of an uncertainty-risk factor into a model of the cross-section of expected stock returns in chapters 5 and 6 (Goyal (2012)).

Intuitively, investors are willing to accept lower returns for stocks that hedge against a deterioration of the expectation of future market returns. This is the *intertemporal hedging demand argument* for why there should be a negative relationship between the correlation of a stock's returns with changes in uncertainty and the stock's expected returns. A stock that tends to have high returns when uncertainty increases, that is when investment opportunities decline, can be used to hedge against such. Since a higher covariance with the risk implies a lower expected return, the risk premium η_i on uncertainty risk in equation 2.3 should be negative. In such cases the literature refers to a *negative price of risk*.

The second line of reasoning for a negative uncertainty premium uses the literature on *uncertainty aversion*. As early as the 1960s, Ellsberg (1961) was able to prove experimentally that people exhibit higher risk-aversion when they are not sure about the probabilities in the game they are playing. Therefore, it can be argued that uncertainty enters investors utility function. In this scenario investors are willing to pay more for stocks that protect them against innovations in uncertainty, because they prefer certainty (Bali, Brown, and Tang (2017)).

This thesis uses implied volatility indices as proxies for unexpected innovations in uncertainty (see section 4.4). Recently, a more direct motivation for a priced expected volatility factor has been published. Campbell et al. (2018) develop a fairly complicated asset pricing model, that most notably allows for heteroskedasticity in returns. They find that dropping the assumption of homoskedasticity introduces *the expectation of future market volatility* as a separate risk factor.[1] However, they do not manage to solve their model for a general equilibrium. Instead, they propose to interpret their model as describing the behavior of individual investors who take heteroskedasticity of returns into consideration when allocating their capital and who, in a market with heterogenous agents, might influence cross-sectional return patterns. This is why Merton (1973) remains the central motivation for an uncertainty factor in the cross-section of expected returns.

4.2 Statistically Motivated Factors

Statistically motivated factors are generally based on the Arbitrage Pricing Theory (APT) of Ross (1976). Without going into the details of the model, Ross proposes

[1] The model does not yield which of these two intertemporal risks, a deterioration of expected market returns or increase in expected volatility, is perceived by investors to be more important. That is, there is no predication whether investors are willing to accept a bigger cut in expected returns for a hedge against a deterioration in investment opportunities or for a hedge against an increase in expected volatility. Campbell et al. (2018) propose to answer this question empirically.

to search the return covariance matrix for common drivers (i.e. factors). All factors discovered this way must represent a systematic risk as non-systematic pricing factors should in equilibrium be arbitraged away. There are several statistical approaches for this, most famously the *factor analysis* of Roll and Ross (1980) and the *principal component analysis* of Connor and Korajczyk (1988) (Goyal (2012)).

One example of a statistically motivated factor that is relevant for this thesis is momentum. Jegadeesh and Titman (1993) reported the *momentum anomaly*: Stocks with higher returns over the past 3 to 12 months tended to outperform over the next month.[2] Momentum has been frequently constructed as a factor (see for example Carhart (1997)), usually by creating a zero-cost portfolio that is long past winners and short past losers. Chapter 3 explained why it is of great advantage to construct factors as tradable portfolios. I mention momentum among the many statistically motivated factors, as it is largely orthogonal to other common risk factors (Jegadeesh and Titman (2002)). Therefore, it is one of the benchmarks most asset pricing studies control for before reporting their results as significant. I do the same in chapter 5, using the Up-Minus-Down (UMD) factor that Kenneth French provides on his website. Also, momentum is special among the famous and robust anomalies in that it seems implausible that it proxies for some non-diversifiable risk. Therefore, momentum is frequently used as an argument against the efficient-markets-hypothesis (see for example Grinblatt and Han (2005)). However, Carhart (1997) finds that transaction costs make momentum-based trading strategies too costly to be profitably exploitable. Thus, momentum as a priced factor can be consistent with the Arbitrage Pricing Theory mentioned above.

Additionally, the *idiosyncratic volatility anomaly* should be mentioned to delimit *idiosyncratic volatility risk* from *implied market volatility risk*. The former describes the tendency of low idiosyncratic volatility stocks (i.e. volatility relative to the predicted return of FF-3, see below) to outperform high idiosyncratic volatility stocks by a surprisingly large margin (1% per month over the period of July 1963 - December 2000) (Ang et al. (2006)). The later describes the tendency of stocks with a high (low) covariance with some proxy for innovations in market uncertainty to earn lower (higher) average returns. Both were famously reported in Ang et al. (2006), the central paper of this thesis, but are found to be independent empirically and in their theoretical motivation. Therefore, this thesis about implied market volatility risk does not concern itself with idiosyncratic volatility risk.

[2] Over longer horizons outperformance of past winners reverses into an outperformance of past losers, hence the name: *reversal effect* (De Bondt and Thaler (1985)).

4.3 Firm Characteristics as Factors

Like momentum and idiosyncratic volatility above, firm characteristics are usually empirically derived as pricing factors. Nonetheless, they deserve special mention due to their huge influence on empirical asset pricing.

The most famous collection of firm characteristic anomalies into one empirical model is Fama and French (1993). They observe that after controlling for exposure to market risk, small stocks (defined by market capitalization) tend to outperform large ones. This *size effect* was originally published in Banz (1981). Second, Fama and French observe that stocks with high book-to-market ratios (*value* stocks) tend to outperform those with low book-to-market ratios (*growth* stocks) This *value premium* was originally published in Rosenberg, Reid, and Lanstein (1985). Out of these observations Fama and French create two new factors in addition to the excess market return into a linear factor equation like 2.3: Small-Minus-Big (SMB) and High-Minus-Low (HML). Again, both are zero net investment portfolios. SMB is the return on such a portfolio that is long small firm stocks and short large firm stocks. HML is the return from being long high book-to-market stocks and short low book-to-market stocks. For the exact factor construction see the caption of table 1 in Fama and French (1996). In the following, I will usually abbreviate this model as *FF-3*. It predicts higher average returns for stocks whose returns positively covary with the market excess return, the SMB factor or the HML factor.

Fama and French (1996) have shown that their 3-factor model can resolve most of the firm-characteristics based market anomalies known at the time. Additionally, the model can explain the reversal effect. Thus, FF-3 became the second model to beat after the CAPM when reporting new findings in the asset pricing literature. I do the same in chapters 5 and 6. However, FF-3 fails miserably when confronted with the momentum effect. That is why I provide separate tests for momentum.

Recently, Fama and French (2015) proposed an extension of their 3-factor model into a 5-factor model. The two new proposed factors are the zero net investment porfolios Robust-Minus-Weak (RMW) and Conservative-Minus-Aggressive (CMA). RMW is long (short) firms with high (low) operating profitability. CMA is long (short) firms that invest conservatively (aggressively). I will usually abbreviate this model as *FF-5*. Although it has not yet become clear whether FF-5 is the new standard to beat, I include RMW and CMA into the robustness tests of the following two chapters. Fortunately, Kenneth French makes SMB, HML, RMW and CMA, together with many supporting data over various frequencies and countries, available on his website, so I do not have to construct these benchmark models myself.

4.4 The Uncertainty Factor

The factors mentioned in subsections 4.2 and 4.3 are empirically successful but unsatisfactory to the researcher in the sense that we do not know which non-diversifiable risk they proxy for. They mainly make a contribution to our understanding of financial markets by highlighting what we do not yet understand, thus motivating much theoretical research.[3] In contrast, section 4.1 gave several theoretical channels through which one can argue for uncertainty-risk as a systematic risk factor. This is what makes the uncertainty factor so exciting. Most notably, Merton (1973)'s ICAPM sees systematic risk both in covariance with the excess market return and in covariance with news about the present value of future market returns.

A broad set of literature provides both theoretical and empirical evidence that increases in aggregate uncertainty are bad news for the present value of future market returns. For example, Bloom (2009) develops a macroeconomic model in which firms react to unexpected increases in uncertainty by delaying investments and hiring, thus leading to a recession-recovery swing in aggregate output and unemployment. His model matches empirical data well.

However, uncertainty cannot be directly observed. Empirical studies of uncertainty, like this thesis, have to decide on a proxy variable. The rest of this section presents a few candidates and uses the opportunity to provide a short and incomplete survey of the literature on uncertainty in the cross-section of expected returns.

Arguably, the first significant paper on an aggregate uncertainty factor is Ang et al. (2006). In the following, I will often abbreviate the paper as *AHXZ*. They use the first-difference of the VXO Index to proxy for innovations in uncertainty. The VXO can be extracted as an implied variable from the Black and Scholes (1973) option pricing formula. This well-known formula requires the volatility of the base-asset's return as one of its inputs. Thus, when everything but volatility is observed for an option contract one can calculate the volatility that would justify the current price according to the formula. This is the *implied volatility*. For a synthetic at-the-money option contract (i.e. the option's strike price is equal to the price of the underlying asset) on the S&P 100 index with a maturity of one month, the Black-Scholes implied volatility is called *VXO* (Whaley (2000)).[4] The VXO is published up to the minute

[3] For example Campbell et al. (2018), whose model was briefly explained above, particularly highlight their model's ability to give a reasonable level of relative risk aversion at which investors would not value-tilt portfolios (i.e. not invest in the HML portfolio) despite higher expected returns.

[4] Up to September 2003, the index described above had the ticker symbol *VIX*. At that time the Chicago Board Options Exchange (CBOE) gave the symbol *VIX* to a new index that uses a broader range of strike prices and represents the implied volatility of a synthetic at-the-money option contract

by the Chicago Board Options Exchange (CBOE). I took the data from the website of Wharton Research Data Services, who refer to the CBOE as their primary source. Figure 4.1 shows the VXO from January 1986 to December 2018.

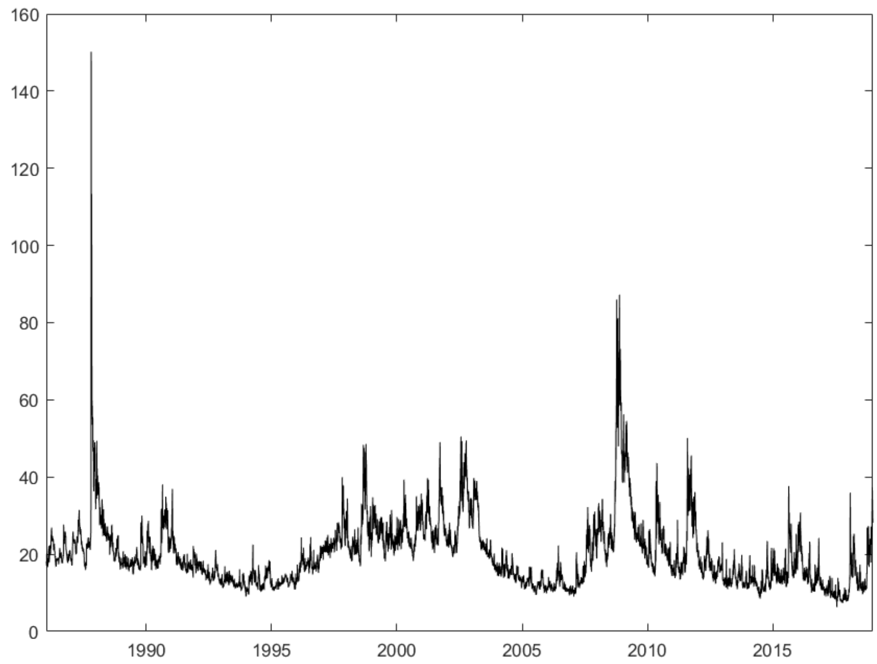

FIGURE 4.1: **VXO: 1986 - 2018**: The figure shows the VXO index at a daily frequency from January 1986 to December 2018. The VXO is the Black-Scholes implied volatility of a synthetic at-the-money option contract on the S&P 100 index with a maturity of 1 month. Data were taken from Wharton Research Data Services.

To measure stocks' potential to provide a hedge against innovations in aggregate uncertainty, *unexpected changes* in uncertainty are of interest, rather than the level of uncertainty. For a time-series like the VXO, obtaining the unexpected changes would usually involve the specification of a model for the conditional mean. The unexpected changes would then be given by the residuals of that model. However, the VXO has a very high first-order autocorrelation (0.97). This can be seen in the form of high persistence in figure 4.1. As a result, the conditional mean in every

on the S&P 500 index. The old index used in this thesis got the ticker *VXO*. Older papers like Ang et al. (2006) refer to what is now known as the VXO by its older ticker VIX, which might lead to some confusion. However, the two are highly correlated (0.98 over 1990-2018) and results generally hold for both. I use the VXO as it is reliably calculated back until 1986, while the VIX is available only from 1990. Backfilling the VIX further is made difficult by some very volatile periods during 1987.

reasonable model for the VXO must always be very close to its unconditional mean. Therefore, Ang et al. (2006) decided to not specify a conditional model, but simply use the VXO's unconditional mean as its expected value. That is, they interpret every change in the VXO as an unexpected one.[5]

AHXZ find a significantly negative relationship between stocks' covariance with this proxy and their average returns over the sample of 1986 to 2000. That is, they use the first-difference of the VXO as a pricing factor in the sense of an x_i in equation 2.3 and find the corresponding η_i to be negative. This is consistent with the intertemporal hedging argument given above: If investors want to hedge against increases in uncertainty, they should be willing to accept lower returns (i.e. pay a higher price) on stocks whose returns positively correlate with proxies for increases in uncertainty. Those stocks would then have lower average returns, which is what AHXZ find.[6] AHXZ show their results to be robust against the inclusion of other common risk factors. For their exact procedure see section 5.1.

Using the VXO as a measure of aggregate uncertainty has two major drawbacks that AHXZ raise themselves. For one, the VXO is based on the Black-Scholes option pricing formula which assumes constant volatility and no jumps in the price of the underlying asset. Both are highly problematic assumptions (Cremers, Halling, and Weinbaum (2015)). If there is a *jump risk* that is priced differently from *volatility risk*, the AHXZ estimation of *volatility risk* may be biased. Cremers, Halling, and Weinbaum (2015) construct orthogonal jump risk and volatility risk factors, test them in the cross-section of expected returns and find a significantly negative relationship between stocks' factor exposure and their average returns for both factors. It seems that jump risk and volatility risk can be constructed as separate factors, but are priced similarly. Thus, this first objection to the proxy used by AHXZ does not seem to be fatal.

The second objection is that implied volatility from option pricing consists of both the expected future volatility and the risk premium investors command for it. Thus, the VXO captures both. If the risk premium on volatility-risk is time-varying, the VXO may not be a good proxy for changes in expected volatility. AHXZ suggest the formulation of a conditional model for the volatility-risk premium to remove

[5] AHXZ report using first-differences of the VXO. However, I was only able to replicate their results when dividing the first-difference by 100. This objection was also raised in Anderson, Bianchi, and Goldberg (2013).

[6] I will frequently refer to stocks whose returns have a relatively high (low) covariance with a proxy for changes in uncertainty as having *high (low) exposure to uncertainty risk*. This is a convention in the literature for any kind of risk. Unfortunately, it makes the argument that stocks with a high exposure to uncertainty risk are bought to reduce the risk from increases in uncertainty sound slightly confusing.

its effects from the VXO, but I have not been able to find any study that does so. Therefore, this objection remains unresolved.

Jurado, Ludvigson, and Ng (2015) econometrically extract the common uncertainty component from 279 mostly macroeconomic time-series. Thus, they avoid the problems with option-based proxies. Bali, Brown, and Tang (2017) test this index in the cross-section of expected returns and find that over the sample of 1972 - 2014 stocks in the highest uncertainty beta decile underperformed those in the lowest decile by a statistically significant 5% per year. Hence, uncertainty has potential as a priced risk factor independent from the Black-Scholes option-based method.

Finally, this section must introduce the *implied treasury volatility index (TYVIX)*. It is calculated by the CBOE since 2013 using a similar method to that described for the VXO, but based on options on 10-year US Treasury Note futures, instead of options on the S&P 100 index. Thus, the TYVIX index captures everything that contributes to volatility in 10-year US Treasury Notes. In particularly, this includes changes in US interest rates (CBOE (2015)).

The index is given for the period of 1986-2018 in figure 4.2. Data have been calculated and made available to me by Paul Whelan. In chapter 6, I use the TYVIX as a proxy for interest rate uncertainty among post-crisis US bank stock returns. The motivation for such a test will be given there. At this point it should only be noted that the correlation with the VXO of 57% as well as the correlation of their first-differences of 12% indicate markedly different informational content in the two indices.

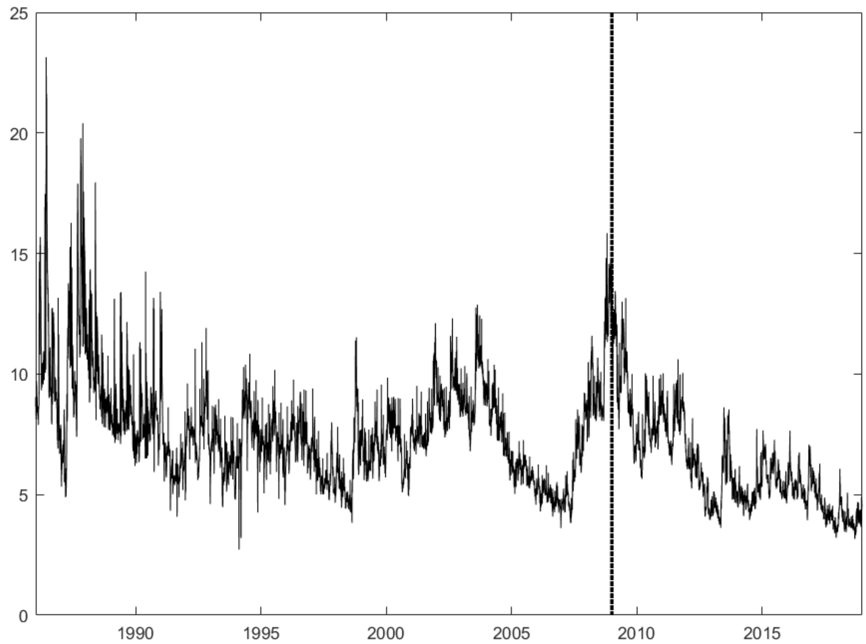

FIGURE 4.2: **TYVIX: 1986 - 2018**: The figure shows the TYVIX index at a daily frequency from January 1986 to December 2018. The TYVIX is the Black-Scholes implied volatility of a synthetic at-the-money option contract on 10-year US Treasury Note futures with one month maturity. The dotted vertical line marks January 2009. The data were calculated and made available to me by Paul Whelan.

Chapter 5

Uncertainty Risk: VXO

Arguably, the first significant paper focusing on the link between aggregate uncertainty and the cross-section of stock-returns was written by Andrew Ang, Robert J. Hodrick, Yuhang Xing and Xiaoyan Zhang and published in 2006 in the Journal of Finance. They find a significant and robust negative relationship between stocks' exposure to uncertainty risk and their average returns over the sample of 1986 to 2000. Thus, their results are in accordance with the theoretical predictions made in chapter 4. Yet, at the time of this thesis there are almost two decades of additional data available, which need to be taken into account when evaluating whether uncertainty risk is priced in the cross-section. Therefore, this chapter is devoted to a replication and subsequent updating of Ang et al. (2006).

To that end, section 5.1 explains the methodology and replicates the results of AHXZ.[1] Replication has the double function of making sure their results can be replicated (i.e. are not due to a faulty implementation on their part) and preventing implementation errors on my part, as a serious factor-analysis consist of numerous inconspicuous steps where junior researchers might make mistakes with far reaching consequences for the validity of results. The elaborations in this section are intentionally detailed, so following sections building on the same methodology can be kept shorter.

This empirical chapter constitutes the culmination of much of the preparatory work in the previous chapters 2, 3 and 4. Therefore, I frequently refer back to their theoretical considerations. Also, due to the replicatory nature of this part of the thesis, section 5.1 is close to AHXZ in both structure and content. Nonetheless, it should be noted that the results reported here are my own and those in AHXZ might deviate slightly.

[1] AHXZ has two parts that are largely independent. I replicate the main results from the first part, which is concerned with uncertainty risk. The second part treats idiosyncratic volatility risk. This is a distinctly different topic and not discussed in this thesis.

Section 5.2 uses the methodology of AHXZ for the period of 1986 to 2018 inclusive, thus updating their study. Over this longer sample, I find the same significant relationship between stocks' exposure to uncertainty risk and their average returns that was reported in AHXZ. However, the support for an uncertainty-risk factor is now less consistent across stocks and smaller in magnitude.

The presented weakening of empirical support motivates section 5.3, where the difference in past average returns for portfolios with different exposure to uncertainty-risk is given for an increasing window from 1990 - 2018. This indicator for a priced uncertainty-risk factor has increased in magnitude until the early 2000, shortly before the publication of AHXZ, and decreased steadily since then.

5.1 A replication of Ang et al. (2006): 1986 - 2000

To uncover the supposed relationship between stocks' expected returns and their sensitivity to innovations in uncertainty, AHXZ provide several interlinked tests, the results of which are summarized in table 5.1.[2]

For the central part of their analysis AHXZ, use all *common stocks* (share code 10 or 11) in the CRSP daily file that were listed on the *NYSE*, *AMEX* or *NASDAQ* between 1986 and 2000 (exchange code 1, 2 or 3). Also, they seem to drop all stocks from the CRSP daily file that are not in the CRSP monthly file (about 300 stocks).[3] Thus, this section considers between 5,604 and 7,403 stocks simultaneously and 15,535 stocks in total.

II: Mean and III: Standard Deviation

For each of these stocks and each month from January 1986 to December 2000, during which the respective stock has at least 17 days with observed returns, I run regression 5.1:

$$r_t^i = \beta_0 + \beta_{MKT}^i MKT_t + \beta_{\Delta VXO}^i \Delta VXO_t + \epsilon_t^i \tag{5.1}$$

, where r_t^i is stock i's simple return from close of day $t-1$ to close of day t, MKT is the market excess return, measured as the CRSP value-weighted daily market index minus the daily risk-free rate reported on Kenneth French's website, ΔVXO is the

[2] The underlined sub-headlines of this section indicate which of table 5.1's columns are described where.

[3] Dropping those stocks is one of the tricks not mentioned in their paper, but necessary to obtain the AHXZ results while following their methodology. This might be one of the reasons why for example Peterburgsky (2016) fails to replicate.

daily first difference of the VXO index measured from close of day $t-1$ to close of day t and divided by 100. β_0 is the intercept of the model and β^i_{MKT} and $\beta^i_{\Delta VXO}$ are stock i's loadings on the respective factor. For a theoretical motivation of this kind of linear factor model see chapter 2 and for a motivation of these specific factors see chapter 4.

Thus, I obtain one uncertainty beta ($\beta^i_{\Delta VXO}$) for each stock and each month. This uncertainty beta measures the degree to which the stock's returns covary with changes in the VXO while controlling for the part of the stock's daily returns that can be attributed to covariation with the excess market return. As discussed in chapter 4 there is a large number of factors that have a claim to being priced in the cross-section of stock returns. To avoid omitted variable bias, equation 5.1 should contain more factors than just the market. AHXZ decided against the inclusion of other factors at this stage, as it might introduce excessive noise into the estimation of $\beta^i_{\Delta VXO}$. Instead, the FF-3 factors, the FF-5 factors and momentum (see chapter 4 for all six) are controlled for in later stages of the analysis.

Re-estimating each stock's sensitivity to innovations in uncertainty every month is the usual compromise between allowing for time-variation in $\beta^i_{\Delta VXO}$ (i.e. re-estimating it as often as possible) and estimating $\beta^i_{\Delta VXO}$ precisely (i.e. using as many observations in each regression as possible) (Ang et al. (2006)).

Individual stocks' average returns are generally too noisy to reject even the hypothesis that all their average returns are equal. Therefore, it is difficult to prove that differences in average returns are driven by a specific risk factor. To reduce this noise, financial economists commonly sort stocks into portfolios depending on their factor exposure and compare average returns of those portfolios (Blume (1970)). I implement this procedure as follows (following AHXZ): At the end of January 1986 the stocks are sorted into 5 *quintile* portfolios depending on their realized $\beta^i_{\Delta VXO}$ over that January, from lowest $\beta^i_{\Delta VXO}$ (portfolio 1) to highest $\beta^i_{\Delta VXO}$ (portfolio 5). The return of those five portfolios over February 1986 is then calculated as the market-value-weighted average of their constituent stocks' returns. At the end of February 1986 the stocks are re-sorted into the 5 portfolios depending on their realized $\beta^i_{\Delta VXO}$ over that February, and so on for every month until December 2000. The necessary monthly stock returns are taken from the CRSP monthly file. Thus, I obtain 179 monthly returns for each of the five portfolios. I will frequently refer to these five as *quintile portfolios* throughout this text. The average of those 179 monthly total (not excess) simple returns is reported for each quintile portfolio in column II of table 5.1, their standard deviation is reported in column III.

Besides reducing the noise in average returns, this procedure of building regularly rebalanced portfolios solves the problem of having an *unbalanced panel*. Since some stocks newly list while others delist from the considered stock exchanges over the given sample not all stocks have return observations for all months. The procedure described above ensures that I have five portfolios with return observations for every day of the sample. This significantly simplifies the analysis.

Table 5.1 shows that the quintile portfolios' average monthly returns decrease monotonically from 1.66% for portfolio 1 (lowest uncertainty-beta stocks) to 0.61% for portfolio 5 (highest uncertainty-beta stocks). This is consistent with the *intertemporal hedging argument* outlined in chapter 4. In short, the *intertemporal hedging argument* for the VXO says that (1) changes in the VXO proxy for changes in uncertainty and (2) higher uncertainty entails a deterioration of investment opportunities, which investors should want to hedge against. If investors do want to hedge against increases in market uncertainty, they should be willing to pay a higher price (i.e. accept a lower return) for stocks whose returns tend to covary more positively with innovations in uncertainty.

Here, the stocks for which this tendency is strongest (weakest) are sorted into portfolio 5 (1). The monotone decline in average returns from portfolio 1 to portfolio 5 indicates that investors are indeed willing to accept lower average returns for the benefit of positive uncertainty betas. In particular, the return on a *5-1 zero-cost portfolio* that goes long portfolio 5 and short portfolio 1 is -1.05% per month and with a t-statistic of -3.97 significantly different from 0 at the 1% level.[4] Thus, the hypothesis, that over the given sample of 1986 to 2000 the returns of stocks with low uncertainty betas and the returns of stocks with high uncertainty betas were drawn from distributions with the same mean, can be rejected. This is a necessary - but not a sufficient - condition for uncertainty risk to be priced in the cross-section of stock returns. Other possible explanations of the difference in average returns need to be ruled out.

First, financial economists are usually interested in risk adjusted returns. That is, mean returns in relation to their standard deviation. Relatively high mean returns that go along with a relatively high standard deviation are generally not regarded as remarkable, as a high standard deviation decreases an investor's expected utility, given a sufficiently concave expected utility function. Column III of table 5.1 shows

[4] All numbers reported in square brackets are heteroscedasticity and autocorrelation robust Newey and West (1987) t-statistics For their calculation a maximum number of time lags has to be chosen at which autocorrelation is to be expected. I follow Bali, Brown, and Tang (2017) and choose a maximum lag of six.

that standard deviations cannot explain the difference in mean returns across quintile portfolios. Portfolios 1 and 5 exhibit higher return standard deviations than 2,3 and 4, which might partially explain the high average returns of portfolio 1, but makes the low average returns of portfolio 5 even more noteworthy.

IV: Market Share

To rule out a second possible explanation see column IV in table 5.1, which reports the average market capitalization of stocks in each portfolio. As mentioned in subsection 4.3, small stocks tend to outperform large ones. Column IV shows that portfolios 1 and 5 contain stocks with a considerably smaller average market capitalization than 2, 3 and 4. Thus, the *size effect* might partially explain the high average returns of portfolio 1, but makes the low average returns of portfolio 5 even more remarkable.[5] The issue of other potential risk-factor explanations for the observed difference in average returns is further addressed below.

VIII: Pre-Formation $\beta_{\Delta VXO}$

Next, it needs to be shown that there is a meaningful dispersion between the $\beta^i_{\Delta VXO}$ that were used to sort stocks into the five portfolios. If the stocks in the five portfolios have basically the same $\beta^i_{\Delta VXO}$, those risk-exposures cannot be used as explanations for differences in average returns. To that end, for each month from February 1986 to December 2000 and for all five portfolios, I calculate the equal weighted average of the previous months $\beta^i_{\Delta VXO}$ of constituent stocks. That is, I calculate the equal weighted average of betas that were used to sort stocks into the quintile portfolios for each month. The time-series average of these cross-sectional monthly averages is multiplied by 100 and reported in the first column under the heading *Factor Loadings* in table 5.1.[6]

To give an example of how these $\beta^i_{\Delta VXO}$ can be interpreted, the 2.20 for portfolio 5 implies that over the sample of 179 months the daily returns of the average firm in

[5] AHXZ also include columns on the average book-to-market ratio and size (measured as average of log market capitalizations) of the stocks in the five portfolios. The former shows that portfolio 1 and 5 contain stocks with a higher book-to-market ratio. A lack of data on the firms' book-values has prevented me from replicating it here. Again, since high b/m stocks tend to outperform low b/m ones (see subsection 4.3) this might partially explain the high average returns of portfolio1, but makes the low average returns of portfolio 5 even more remarkable. The *size* column is not replicated here as it provides no additional insight after looking at market capitalizations.

[6] AHXZ, report to value-weight the past-month $\beta^i_{\Delta VXO}$. Yet, this leads to different numbers, while using equal-weighted betas allows for an exact replication of their results. Therefore, I am using equal-weighted betas. They probably made the decision to multiply all betas by 100 before reporting them to avoid the excessive use of zeros in their table.

portfolio 5 during the month before it was sorted into portfolio 5 increased on average by 0.00022 when the first-difference of the VXO increased by 1, after controlling for an intercept and the excess market return.[7] [8]

Thus, these *average pre-formation* $\beta^i_{\Delta VXO}$ measure the degree to which the five portfolios' varying stocks tended to covary with innovations in uncertainty during the month before they were sorted in the their respective portfolio. While the monotone increase in these betas from portfolio 1 to portfolio 5 is by design, the magnitude of this increase is satisfactory. The attempt to regularly re-sort stocks into portfolios depending on their past exposure to innovations in uncertainty seems to have succeeded.

X: Next Month Post-Formation $\beta\Delta VXO$

However, returns (in column II) are measured over the month post-formation. Therefore, it is of interest to see that stocks sorted into portfolio 1 (5) also have lower (higher) $\beta^i_{\Delta VXO}$ over the month *post*-formation. AHXZ change their approach to calculating the portfolios' average uncertainty betas post-formation relative to pre-formation. For post-formation betas, they calculate daily portfolio returns as the value-weighted average of returns of their constituent stocks each month, and report the $\beta^i_{\Delta VXO}$ (multiplied by 100) from linear regressions of these daily portfolio returns minus the risk-free rate on ΔVXO_t and the excess market return. In other words, they are estimating regression 5.1 for the quintile portfolios. The dispersion in next-month post-formation $\beta^i_{\Delta VXO}$ thus calculated is reported in the second-to-last column of table 5.1.

The magnitude of these betas is disappointingly low. Over the given sample, a one unit increase in the daily first-difference of the VXO on average coincided with a decrease in the daily return on portfolio 1 of $3.4 * 10^{-6}$ and an increase in the daily return on portfolio 5 of $6.8 * 10^{-6}$ after controlling for an intercept and the excess return on the market. Furthermore, the monotone increase from portfolio 1 to 5 has disappeared.

As an additional test, I used the procedure described above for pre-formation $\beta^i_{\Delta VXO}$ to calculate post-formation $\beta^i_{\Delta VXO}$. The results are even less supportive for an uncertainty-risk factor (similar magnitude, but no pattern across quintile portfolios), which might be a reason AHXZ changed the approach.

[7] Two zeros in front of 2.2 arise because coefficients are reported multiplied by 100 in table 5.1, two further zeros arise because ΔVXO is divided by 100 before including it into regression 5.1.

[8] I am aware that this interpretation does not read fluently. This might be the reason why AHXZ do not provide any such interpretation of their betas.

Thus, both approaches described above show hardly any difference between the uncertainty betas of stocks sorted into portfolio 1 and stocks sorted into portfolio 5 during the month after they have been sorted. This, however, is the month over which average returns are reported in column II. For a factor explanation of the difference in average returns it would be necessary to find a simultaneous relationship between higher sensitivity to changes in the VXO and lower average returns. The failure to find strong supportive evidence for such a simultaneous relationship here is a serious objection to any claim that innovations in the VXO are priced in the cross-section of stock returns. The issue of uncovering a supposed *simultaneous* relationship between exposure to uncertainty-risk and average returns is further addressed below.

V: CAPM Alpha

Near the beginning of this subsection I mentioned the problem of not taking into account other well-known cross-sectional risk-factors when estimating a stock's exposure to innovations in the VXO. This problem is remedied here. To prove that the difference in average returns reported in column II of table 5.1 cannot be explained by these other risk-factors, I execute 10 additional regressions (following AHXZ). First, the 179 monthly returns of each of the 5 quintile portfolios are regressed on the excess market return (MKT). The intercepts of these regressions are reported in column V, together with robust Newey and West (1987) t-statistics. As this procedure was pioneered by Jensen (1968), the intercepts are commonly referred to as *Jensen's alphas*. Due to the nature of linear regressions, the part of monthly returns of each portfolio that cannot be explained by covariation with the market factor (i.e. by the CAPM, see subsection 4.1) ends up in the respective intercept. That is, of the 1.66% average monthly return on portfolio 1, 0.27 percentage points cannot be explained by the CAPM. For the intercepts to be interpreted as pricing errors of the CAPM it is crucial that the factor tested (here MKT) is itself a traded portfolio. This condition is fulfilled for MKT, as well as the FF-3 and FF-5 factors below. For a detailed explanation of the *traded portfolio condition* see section 3.1.

The t-statistics tests whether the hypothesis that the respective intercept is equal to zero can be rejected. In order to reject at the 5% significance level, the t-stat would need to exceed 1.97, as each regression has 177 degrees of freedom and this is a two-sided test. Column V shows that the hypothesis of no intercept against a two sided alternative can only be rejected on the 5% significance level for portfolio 5 and the 5-1 zero-cost portfolio. This result constitutes a further problem for the claim of an uncertainty risk-factor in the cross-section of stock returns. In order to validate such a claim, I would need to be able to reject the hypothesis that conventional risk-factors, like the CAPM, can explain the average returns of portfolios that differ greatly in their exposure to uncertainty risk (see column 1 under the heading *Factor Loadings*). In column V, I fail to do so. At least, the return on the 5-1 portfolio has a significant unexplained component. So, this test is not absolutely fatal. Also, the monotone decline in intercepts from portfolio 1 to portfolio 5 is encouraging. Such a continuous change from unexplained positive component in average returns for portfolios that covary negatively with innovations in uncertainty to an unexplained negative component in average returns for portfolios that covary positively with innovations in uncertainty is what one would expect to find if investors used the later to hedge against a deterioration in investment opportunities.

Finally, AHXZ calculate the test of Gibbons, Ross, and Shanken (1989) for joint significance of all 5 alphas (excluding the 5-1 alpha). I replicate the test and report the corresponding p-value in the last row of table 5.1. With a p-value of 0.01, I reject the hypothesis that all alphas in column V are equal to 0. As a conclusion of column V, there seems to be something in the average returns that is not explained by the CAPM, although the evidence is not overwhelming.

VI: FF-3 Alpha and VII: FF-5 Alpha

Chapter 4 has shown that the market factor is by no means the only linear risk-factor to be taken into account when proposing the inclusion of a new risk dimension into cross-sectional asset pricing. As a result, AHXZ next regress the 179 monthly returns of the quintile portfolios on the Fama-French 3 factors: MKT, SMB and HML. The alphas of my replication are reported in column VI. I add a regression for each portfolio on the Fama-French 5 factors: MKT, SMB, HML, CMA and RMW. Those alphas are reported in column VII. CMA and RMW were published in 2015 and therefore not known to AHXZ when publishing their paper on uncertainty-risk. For a motivation of all these factors and references to both the literature and data see subsection 4.3. For correlations of these and other factors with ΔVXO at the monthly frequency see table 5.2.

On the positive side, the monotone decline in intercepts from portfolio 1 to portfolio 5 remains largely intact for both the 3- and 5-factor asset pricing model (the exception are portfolio 3 and 4 in FF-5). Additionally, the t-statistics show that the average returns of the 5-1 portfolio have a significant unexplained component on the 5% level in comparison to FF-3 and on the 10% level in comparison to FF-5. On the other hand, the t-stats of all portfolios, with the exception of portfolios 5 and 5-1, are disappointingly low. For none of them I can reject the hypothesis that they are equal to 0 and thus that there is actually nothing to be explained here that wasn't covered by Fama and French (1993) or Fama and French (2015). Moreover, the *joint test p-values* in the last row does not allow for a rejection (on a 5% significance level and against a two-sided alternative) of the hypothesis that all alphas are equal to 0.

AHXZ take column V and VI (they did not have VII) as strong support for a significant uncertainty-risk factor in the cross-section. I suggest a more cautions interpretation. The largely significant 5-1 portfolio t-statistics, in conjunction with the largely monotone decline in these intercepts from low- to high- uncertainty-risk portfolios, suggest there might be something here that is not explained by traditional risk factors and this *something* might be uncertainty-risk. However, the evidence is not overwhelming. Further tests, and possibly more data, are needed to take such a conclusion. This is what the rest of this thesis is for.

IX: Pre-Formation $\beta FVXO$

As before, the subject of *simultaneity* has to be addressed in connection with these intercept-tests. The alphas result from regressions of monthly portfolio returns on risk-factors over the whole sample of February 1986 to December 2000. To be able to argue that the monotone decline in alphas from portfolio 1 to portfolio 5 might at least partially be explained by the portfolios' different exposure to systematic volatility-risk, I need to measure this exposure over the same period as the alphas (i.e. the whole sample). This poses a challenge. While the first-difference of the VXO is well suited to proxy for unexpected innovations in uncertainty at the daily frequency (see section 4.4), the high persistence apparent from figure 4.1 makes it a very bad proxy at the monthly frequency.

AHXZ solve this problem by building a new factor from the existing quintile portfolios. Following Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001), AHXZ and I rebalance the five portfolios every month so as to make the daily returns of the resulting combined portfolio match daily innovations in the VXO over that month as closely as possible. This combined portfolio is commonly called the *factor mimicking portfolio*. Its daily returns constitute the new factor that is supposed to capture innovations in market-wide uncertainty. I will call this factor $FVXO$.

To give its construction more formally, see equation 5.2

$$\Delta VXO_t = c + b' X_t + u_t \tag{5.2}$$

, where ΔVXO_t is the daily first-difference of the VXO index, X_t is the 5x1 vector of quintile portfolio returns during day t, b' is the 1x5 vector of estimated weights, c is the intercept and u_t are the residuals of the model. If equation 5.2 is estimated via OLS at the daily frequency every month, the $FVIX$ factor for day t is given as $b'X_t$. Innovations in uncertainty at any frequency can now be calculated by aggregating the appropriate daily changes in the $FVIX$.

It should be noted that, while FVXO is constructed from the returns of traded assets, it is not itself an *investable* portfolio, since, for example, the $FVXO$ portfolio during February 1986 is constructed to best match the daily first-difference in the VXO index during that month. However, the daily innovations in the VXO during February 1986 could not have been known in advance. Thus, the FVXO index is constructed using future information.

As a first application of this new factor, AHXZ want to make sure that the mimicking of VXO at the daily frequency worked in so far as the stocks in the quintile portfolios have a similar exposure to the FVXO at the daily frequency over the month before they are sorted into their respective portfolios as they had to the first difference of the VXO. To answer this question, they follow the same steps that led to the first column under the heading *Factor Loadings* in table 5.1 (see above), only applying FVXO instead of VXO at every step. The sorting of stocks into the five portfolios at the end of each month is still based on their covariance with ΔVXO to make sure that we are still dealing with the same portfolios.

As in this entire section, I replicate their procedure. The resulting coefficients are reported, multiplied by 100, in the second column under the heading *Factor Loadings*. The similarity of those five numbers to the ones reported to their left reveals that the average firm in each portfolio has a similar daily covariance with FVXO and ΔVXO. This similarity is consistent with a 91 % correlation between ΔVXO and FVXO at the daily frequency.

XI: Next Month Post-Formation $\beta FVXO$

Now, the above mentioned question, whether the quintile portfolios have different exposures to uncertainty risk at the same frequency (monthly) and over the same period over which the pricing errors were given in columns V to VII, can finally be addressed directly. To that end, AHXZ regress the monthly quintile portfolio returns on an intercept, the FF-3 factors and the FVIX factor, divided by 100, at the monthly frequency.

The $\beta^i_{\Delta FVXO}$ coefficients from these regressions are reported, multiplied by 100, in the last column of table 5.1, together with the usual robust t-statistics. To give an exemplary interpretation, the first row of this column implies that, from February

1986 to December 2000, the monthly return of portfolio 1 decreased on average by 0.052 when the FVXO increased by 100, controlling for the FF-3 factors.

As before, the exact numbers are not of interest. Instead, it is crucial to find a monotone decline in FVXO betas from portfolio 1 to 5 and the zero-hypothesis can be rejected both for each individual coefficient (see t-values in square brackets) and jointly for all coefficients (see p-value in the last row). This reveals a significant increase in exposure to uncertainty risk from portfolio 1 to 5 over the same sample and at the same frequency over which column V to VII reported a mostly significant decrease in standard-model-pricing-errors. If the theoretical motivations of an uncertainty factor in the cross-section put forward in chapter 4 were correct, this is what one would expect to find.

Thus, a causal relationship between a stock's exposure to innovations in uncertainty and its expected return can at least not be ruled out at this point. However, before making a positive conclusion there remain a battery of robustness tests and an update to current data.[9]

[9] This seems to be as good an opportunity as any to point out that the development of MATLAB code that replicates Ang et al. (2006) was associated with considerable effort and should be considered as a vital part of this thesis. The code is available upon request.

TABLE 5.1: **ΔVXO in the Cross-Section of Stock returns: 1986 - 2000**

For each month from January 1986 to December 2000 the daily returns of all NYSE, NASDAQ and AMEX stocks are regressed on MKT and ΔVXO. The stocks are then divided into 5 portfolios from lowest $\beta^i_{\Delta VXO}$ (portfolio 1) to highest $\beta^i_{\Delta VXO}$ (portfolio 5). Thus, the 5 portfolios are rebalanced at the end of each month. Their monthly returns are given as the value-weighted average of their current constituents. Column II reports the average and column III the standard deviation of the 179 monthly total (not excess) returns for each portfolio, as well as a zero-cost portfolio that goes long portfolio 5 and short portfolio 1. Column IV gives their average market share. Columns V to VII contain the intercepts in monthly regressions of the portfolio returns on the market return, the FF-3 factors and the FF-5 factors, respectively. They can be interpreted as pricing errors of the respective model. Column 1 under the sub-heading *Factor Loadings* reports the time-series average of equal-weighted monthly averages of $\beta^i_{\Delta VXO}$ of consitituent stocks for each portfolio. The third-to-last column gives the same for $\beta^i_{\Delta FVXO}$, with FVXO being the daily factor constructed by monthly rebalancing the 5 portfolios so as to match daily innovations in the VXO as closely as possible. In contrast to the two preceding columns, the second-to-last column reports the time-series average of the monthly $\beta^i_{\Delta VXO}$ of the portfolios directly, while controlling for the market factor. The last column reports the $\beta^i_{\Delta FVXO}$ coefficients in the regression of monthly portfolio returns over the whole sample on a constant, the FF-3 factors and the FVXO factor. Square brackets contain robust Newey-West t-statistics. The *joint-test p-values* are based on an F-test by Gibbons, Ross, and Shanken (1989).

							Factor Loadings			
I Rank	II Mean	III Std. Dev.	IV % Mkt Share	V CAPM Alpha	VI FF-3 Alpha	VII FF-5 Alpha	Pre-Formation $\beta\Delta$ VXO	Pre-Form. β FVXO	Next Month Post-Form. $\beta\Delta$ VXO	Next Month Post-Form. β FVXO
1	1.66	5.56	9.3%	0.27	0.31	0.35	-2.10	-2.01	-0.034	-5.2
				[1.52]	[1.69]	[1.61]				[-4.06]
2	1.37	4.42	28.8%	0.15	0.05	0.02	-0.46	-0.42	-0.34	-2.92
				[1.60]	[0.75]	[0.20]				[-2.73]
3	1.33	4.39	30.5%	0.1	0.04	-0.07	0.03	0.08	0	-1.58
				[0.97]	[0.49]	[-1.07]				[-2.90]
4	1.22	4.78	24.0%	-0.08	-0.08	-0.05	0.54	0.61	0.024	3.42
				[-0.95]	[-0.84]	[-0.48]				[5.26]
5	0.61	6.60	7.4%	-0.89	-0.52	-0.38	2.20	2.28	0.068	8.85
				[-3.22]	[-2.42]	[-1.68]				[4.67]
5-1	-1.05			-1.16	-0.83	-0.73				
	[-3.97]			[-3.27]	[-2.60]	[-1.85]				
Joint test p-value				0.01	0.06	0.05				0.00

5.1.1 Properties of the FVXO Factor: 1986 - 2000

This subsection investigates the relation of the new FVXO factor to existing risk-factors. For that purpose, table 5.2 presents the correlation of FVXO with ΔVXO at a daily frequency in panel A and the correlation with common risk-factors on a monthly frequency in panel B. In addition, the table contains the daily and monthly means and standard deviations of both FVXO and VXO. Here, the *common risk-factors* include the momentum factor UMD (Up-Minus-Down) from Kenneth French's website and Pástor and Stambaugh (2003)'s liquidity factor LIQ from Robert Stambaugh's website, in addition to the FF-3 and FF-5 factors, whose sources were already given in Ch 4.

The high contemporaneous correlation between FVXO and ΔVXO at a daily frequency shows that the replication of the later by monthly rebalancing the quintile portfolios (see above) worked reasonably well. The markedly lower correlation at a monthly frequency together with twice the standard deviation at least suggests that there might have been a benefit to constructing FVXO instead of using the monthly innovations in the VXO directly. The very low means of ΔVXO are to be expected when taking the first-difference of a largely stationary time-series (see figure 4.1).

FVXO has a high negative correlation with the excess return on the market portfolio and the liquidity factor. As Ang et al. (2006) point out, the former is consistent with the negative relationship between market volatility and market returns, while the later can be explained via Pástor and Stambaugh (2003)'s construction of the liquidity factor. They built their liquidity-mimicking portfolio in such a way that LIQ decreases when market liquidity rises. Since times of low market liquidity are usually also times of high volatility (Hameed, Kang, and Viswanathan (2010)), FVXO and LIQ are strongly negatively correlated.

However, neither the correlation with MKT, nor with LIQ is high enough to justify fears FVXO might not bring new information to the table. Such fears are even less justified in connection to the remaining risk factors. FVXO is almost orthogonal to SMB and RMW at the monthly frequency and the absolute value of correlations with HML, UMD and CMA never exceeds a third.

These low cross-correlations simultaneously suggest that FVXO contains information that are lacking in the considered existing factors and that the potential problem of *multicollinearity* when estimating factor exposures would only be of minor importance in an asset pricing model that combines FVXO with any of the given factors.

TABLE 5.2: **Factor Correlations: VXO 1986 - 2000**

On the left side, the mean and standard deviation of both the first-difference of the VXO and of the FVXO factor are given at the daily (top) and monthly (bottom) frequency. On the right side, their contemporaneous correlations with each other are given at the daily (panel A) and monthly (panel B) frequency . In addition, panel B contains correlations with common cross-sectional risk-factors. MKT, SMB and HML were proposed in Fama and French (1993). CMA and RMW were proposed in Fama and French (2015). UMD was constructed by Ken French. All seven can be found on his website. LIQ was proposed in Pástor and Stambaugh (2003) and can be found on Robert Stambaugh's website.

			Panel A: Daily Correlations								
	Mean	Std dev	FVXO	Δ VXO							
Δ VXO	0.00	2.65	0.91	1.00							
FVXO	0.03	2.49	1.00	0.91							
			Panel B: Monthly Correlations								
			FVXO	Δ VXO	MKT	SMB	HML	UMD	LIQ	RMW	CMA
Δ VXO	0.07	4.85	0.70	1.00	-0.58	-0.17	0.20	-0.11	-0.37	0.16	0.26
FVXO	0.66	11.55	1.00	0.70	-0.66	-0.13	0.24	-0.26	-0.48	0.07	0.3

5.1.2 ΔVXO Robustness Tests: 1986 - 2000

The number of robustness tests necessary before including a new risk-factor into the canon of asset pricing exceeds the restrictions of a master thesis by a large margin. AHXZ test the robustness of their results to (I) different conditional means of the VXO, (II) the quintile portfolio formation window, (III) the size-effect, (IV) the value-effect (see chapter 4 for both), (V) liquidity effects, (VI) trading volume and (VII) momentum. I limit myself to VII as momentum is arguably the most famous return factor that is not captured by either FF-3 or FF-5 (see chapter 4).

To that end, I perform a procedure that is known as *double-sorting*. At the end of each month from January 1986 to December 2000, I sort all stocks in the CRSP daily file into five portfolios, depending on their return over the past 12 months. I calculate the past 12-month return for each stock and each month by aggregating the appropriate monthly returns from the CRSP monthly file. Then, I further divide each of these fifths into five portfolios depending on their $\beta_{\Delta VXO}$ over the past month in the manner described above. Thus, I obtain 25 portfolios for each month. Linking, for example, all portfolios with the highest return over the previous 12 months and the highest $\beta_{\Delta VXO}$ over time, allows for the calculation of average returns over the whole sample. In other words, I execute the exact monthly re-sorting of stocks into portfolios depending on their exposure to uncertainty-risk that was described above, with the one difference that each month I first divide the stocks into fifths by their previous 12-month return.

Afterwards each five portfolios with different momentum but same past uncertainty beta sorting are combined, thus resulting in five portfolios to analyze. Again, the stocks' returns are value weighted within each portfolio. Table 5.3 reports results obtained via the procedures described above. For example, the *rank 1* portfolio each month contains the portfolio with the smallest exposure to uncertainty-risk out of each momentum fifth. This way, the outperformance of high momentum stocks should not confound my analysis any more, as I compare five portfolios (rank 1 to 5) with different $\beta_{\Delta VXO}$ that have roughly the same previous 12-month returns.

The first remarkable result from double-sorting by momentum and $\beta_{\Delta VXO}$ apparent from table 5.3 is a reduction in average returns of all five portfolios. This is surprising, but might be explained by high-return stocks being sorted into portfolios where value-weighting puts relatively less weight on their returns.

More relevant to the question of uncertainty-risk, the 5-1 spread has decreased to -0.89% per month. However, this is still a large underperformance of high uncertainty-risk-exposure stocks and with a robust t-statistic of -4.6 highly statistically significant. The *Pre-Formation* $\beta_{\Delta VXO}$ have remained almost the same, indicating a successful sorting by $\beta_{\Delta VXO}$ and a sufficient spread in risk-exposures pre-formation to identify effects of uncertainty-risk exposure on average returns.

In contrast, the *Next Month Post-Formation* β_{FVXO} have changed markedly. They are now all positive and those of portfolios with rank 1-3 are not significantly different from zero any more. Yet, the monotone increase in exposure from rank 1-5 remains intact and the hypothesis of joint insignificance can be rejected. Thus, the portfolios retain a sufficient spread in uncertainty-risk exposures on a monthly frequency and over the whole sample. This gives meaning to the pricing errors.

In accordance with the much lower average returns on all five portfolios, all pricing errors are now negative. More importantly, the CAPM, FF-3 and FF-5 intercepts do not show a monotone decline from rank 1 to 5 any more. For all three benchmark models, intercepts increase from 1 to 3 and decrease from 3 to 5. Thus, at least some of the monotone declines in pricing errors found in section 5.1 seem to be explained by momentum effects. However, the 5-1 portfolio still has a large negative unexplained monthly pricing error relative to all three models and its robust t-statistics even increased to levels where equality to zero can be rejected on the 1% level. Also, the hypothesis of all alphas being jointly zero can now be rejected for all three models.

Thus, momentum seems to play a role for the results of AHXZ. Especially the pricing errors of low uncertainty-risk portfolios (rank 1 and 2) change their relative behavior to the other portfolios when controlling for momentum. At the same time, the central results prove robust. There remains a highly significant negative return on the 5-1 zero-cost portfolio, that remains significantly negative when applying the three benchmark models of empirical asset pricing. As a result, this robustness test does not invalidate the findings of AHXZ.

TABLE 5.3: **ΔVXO in the Cross-Section of Stock returns: 1986 - 2000, controlling for Momentum**

For each month from January 1986 to December 2000, the daily returns of all NYSE, NASDAQ and AMEX stocks are regressed on MKT and ΔVXO. Each month, the stocks are divided into five portfolios depending on their return over the previous 12 months and within each of these fifths further divided depending on their $\beta^i_{\Delta VXO}$. Finally, the lowest $\beta^i_{\Delta VXO}$ portfolio from each past-return portfolio are combined into a portfolio of rank 1, the second lowest into rank 2 and so forth. Returns are value-weighted within each portfolio. Column II reports the average and column III the standard deviation of the 179 monthly total (not excess) returns for each portfolio. Columns IV to VI contain the intercepts in monthly regressions of the portfolio returns on the market return, the FF-3 factors and the FF-5 factors, respectively. Column VII reports the time-series average of equal-weighted monthly averages of $\beta^i_{\Delta VXO}$ of consitituent stocks for each portfolio. The last column reports the $\beta^i_{\Delta FVXO}$ coefficients in the regression of monthly portfolio returns over the whole sample on a constant, the FF-3 factors and the FVXO factor. FVXO is the daily factor constructed by monthly rebalancing the 5 portfolios so as to match daily innovations in the VXO as closely as possible. Square brackets contain robust Newey-West t-statistics. The *joint-test p-values* are based on an F-test by Gibbons, Ross, and Shanken (1989).

						Factor Loadings	
Rank	Mean	Std. Dev.	CAPM Alpha	FF-3 Alpha	FF-5 Alpha	Pre-Form $\beta\Delta$ VXO	Next Month Post-Form β FVXO
1	1.23	6.58	-0.15	-0.19	-0.15	-2.06	0.28
			[-0.85]	[-1.22]	[-1.07]		[0.2]
2	1.25	5.68	-0.04	-0.15	-0.14	-0.49	0.88
			[-0.29]	[-1.26]	[-1.37]		[0.64]
3	1.26	5.69	-0.02	-0.12	-0.11	0.03	1.32
			[-0.14]	[-1.19]	[-1.14]		[1.02]
4	1.04	5.7	-0.25	-0.31	-0.29	0.57	5.12
			[-2.16]	[-2.7]	[-2.23]		[5.51]
5	0.34	6.6	-1.08	-0.93	-0.83	2.14	7.69
			[-4.91]	[-4.72]	[-3.96]		[5.61]
5-1	-0.89		-0.93	-0.74	-0.68		
	[-4.6]		[-3.67]	[-3.4]	[-2.62]		
Joint test p-value			0.00	0.00	0.00		0.00

This section closes with some suggestions for further robustness tests, that might be followed up in a more complete study. First, ANXZ chose a 12-month window to control for momentum effects and I follow their procedure. However, I would have chosen a shorter window, as 12 months is the upper limit on which momentum has manifested itself historically (see chapter 4).

Also, the analysis of this chapter is based on quintile portfolios, while the number of stocks considered would easily allow for the construction of decile portfolios. Decile portfolios should show the same patterns found above if uncertainty-risk is a priced factor.

Finally, DeLisle, Doran, and Peterson (2011) find uncertainty risk to be priced in the cross-section only when implied market volatility rises, but not when implied volatility declines. Yet, they apply a different procedure with significantly less stocks. It would be of interest to see whether the AHXZ procedure also yields such an asymmetrical pricing.

5.2 Extending the Sample of Ang et al. (2006): 1986 - 2018

Section 5.1 yielded promising results for the inclusion of uncertainty-risk into cross-sectional asset pricing models. However, only data from 1986 to 2000 were considered. Since then almost two decades have passed. This section applies the exact same methodology to the sample of 1986 to 2018. As mentioned in the introduction to this chapter, section 5.1 was explained in great detail. I will not re-state every step of the analysis here. Instead I will focus on the differences in procedure and the interpretation of results.

Regarding procedure, AHXZ temporarily dropped a stock from the sample when it did not have at least 17 daily return observations during that month. Here, this approach would lead to the exclusion of all stocks during September 2001. Therefore, I lower the barrier to at least 14 daily return observations.[10]

The results of this updated analysis are reported in table 5.4. Column II shows that all quintile portfolios have lower average returns considering the additional 18 years. This is not surprising since 2001 to 2018 was generally a less successful time for equities than 1986 to 2000. Again, the absolute height of average returns is of less interest than their dispersion. Here, the indications that uncertainty-risk might be priced in the cross-section have weakened.

On the one hand, the 5-1 zero-cost portfolio on average earned a monthly return of -0.58% and this return is different from zero at the 5% significance level against

[10] To make sure that this small change in procedure does not have any influence on my results, I implemented the 14 day barrier over the AHXZ-period of 1986 to 2000. This changes the results reported above in their second decimal point at most. Thus, this change in procedure can safely be ignored when interpreting results.

a two-sided alternative (see t-statistic). This is in support of the risk-story that I am testing here.

On the other hand, this negative relationship between stocks' exposure to ΔVXO and their average returns is purely driven by portfolios 1 and 5. There is hardly any difference in average returns between portfolios 2, 3 and 4. Also, the monotone decline from 1 to 5 does not hold any more.

The standard deviations of quintile portfolio returns and average market shares of their constituent stocks, reported in columns III and IV respectively, stay very close to their old patterns. Portfolios 1 and 5 tend to consist of smaller stocks, whose returns have a higher standard deviation, while portfolios 2, 3 and 4 do not differ much along either dimension. Same as above, the high standard deviations and low market shares might constitute a partial explanation of the high average returns of portfolio 1, but make the low average returns of portfolio 5 more remarkable.

The same similarity to the results reported above holds for columns 1 and 3 under the *Factor Loadings* heading. Column 1 gives each portfolios' constituent stocks average daily covariance with innovations in the VXO during the month before they were sorted into their respective portfolios. This column shows a satisfactory dispersion in average exposures. Column 3 does not concern itself with individual stocks, but reports each portfolios' daily return covariance with innovations in the VXO directly over the month after their construction. As for 1986 to 2000, the results over 1986 to 2018 are disappointing. There is hardly any dispersion in uncertainty-risk exposure between the portfolios over each post-formation month. This puts into question whether such an exposure can explain the distribution of mean returns in column II.

The intercepts in the regressions of 395 monthly portfolio returns for each portfolio on the excess market return (i.e. the pricing errors of the CAPM when confronted with the quintile portfolios) are a little more encouraging. Although there is hardly any difference between the intercepts of portfolios 1 to 4 and none of those is different from zero at common significance levels, the 5-1 portfolio has a highly negative unexplained component that is significant at the 1% level and the hypothesis of all intercepts being jointly zero can be rejected (see p-value in the last row).

The intercepts and t-stats of the FF-3 model reported in column VI are remarkably close to those of the CAPM. Covariation with SMB and HML seems to explain almost no component of the quintile portfolio average returns over the period of 1986 to 2018 after the MKT factor has been controlled for. In contrast, the inclusion of CMA and RMW into the regressions has a noticeable influence (see column VII). The intercepts of quintile portfolios 1-4 are now indistinguishable from zero and what is most important, neither portfolio 5 nor 5-1 are significant at the 5% level any more. Even the hypothesis of intercepts 1 to 5 all being zero cannot be rejected.

Considering columns V to VII together, Portfolios 1 to 4 do not have abnormal returns in relation to either of the three models considered and much of portfolio 5's low average returns seems to be explained by exposure to RMW and CMA instead of a high covariance with ΔVXO. At this point it is clear that this thesis will not conclude in a wholehearted embrace of the idea of a priced uncertainty-risk factor in the cross-section of stock returns.

On the positive side, the construction of a factor-mimicking FVXO portfolio seems to have succeeded just as well as before. On a daily frequency over the pre-formation months, the five portfolios' average exposure to FVXO (second *Factor Loadings* column) is similar to the average exposure of their constituent stocks to ΔVXO over the same months (first *Factor Loadings* column).

Thus, the last column can be trusted. It reports the quintile portfolios' covariances with FVXO at a monthly frequency over the whole sample and after controlling for MKT, SMB and HML. The monotone decline in coefficients from portfolio 1 to 5 with throughout significant t-stats and a rejection of the *jointly 0* hypothesis, demonstrates a sufficient dispersion in uncertainty-risk exposure of the quintile portfolios over the same period and at the same frequency that was used to calculate the alphas in columns V to VII.

However, this is mainly positive information regarding methodology. It does not change the disappointingly low, insignificant pricing errors and in some ways it makes them worse. As the construction of portfolios with a diverse exposure to uncertainty-risk seems to have succeeded, the alphas would have shown the characteristic pattern of mispricings (see above), if there was any such pattern to uncover. Since they do not show such a pattern, it stands to reason that there is nothing to uncover and uncertainty-risk is not a priced risk-factor.

TABLE 5.4: **ΔVXO in the Cross-Section of Stock returns: 1986 - 2018**

For each month from January 1986 to December 2018 the daily returns of all NYSE, NASDAQ and AMEX stocks are regressed on MKT and ΔVXO. The stocks are then divided into 5 portfolios from lowest $\beta^i_{\Delta VXO}$ (portfolio 1) to highest $\beta^i_{\Delta VXO}$ (portfolio 5). Thus, the 5 portfolios are rebalanced at the end of each month. Their monthly returns are given as the value-weighted average of their current constituents. Column II reports the average and column III the standard deviation of the 395 monthly total (not excess) returns for each portfolio, as well as a zero-cost portfolio that goes long portfolio 5 and short portfolio 1. Column IV gives their average market share. Columns V to VII contain the intercepts in monthly regressions of the portfolio returns on the market return, the FF-3 factors and the FF-5 factors, respectively. They can be interpreted as pricing errors of the respective model. Column 1 under the sub-heading *Factor Loadings* reports the time-series average of equal-weighted monthly averages of $\beta^i_{\Delta VXO}$ of consitituent stocks for each portfolio. The third-to-last column gives the same for $\beta^i_{\Delta FVXO}$, with FVXO being the daily factor constructed by monthly rebalancing the 5 portfolios so as to match daily innovations in the VXO as closely as possible. In contrast to the two preceding columns, the second-to-last column reports the time-series average of the monthly $\beta^i_{\Delta VXO}$ of the portfolios directly, while controlling for the market factor. The last column reports the $\beta^i_{\Delta FVXO}$ coefficients in the regression of monthly portfolio returns over the whole sample on a constant, the FF-3 factors and the FVXO factor. Square brackets contain robust Newey-West t-statistics. The *joint-test p-values* are based on an F-test by Gibbons, Ross, and Shanken (1989).

							Factor Loadings			
I Rank	II Mean	III Std. Dev.	IV % Mkt Share	V CAPM Alpha	VI FF-3 Alpha	VII FF-5 Alpha	Pre-Formation $\beta\Delta$ VXO	Pre-Form β FVXO	Next Month Post-Form $\beta\Delta$ VXO	Next Month Post-Form β FVXO
1	1.09	5.49	10.4 %	0.08	0.11	0.14	-1.79	-1.70	-0.008	-2.85
				[0.65]	[-0.84]	[1.01]				[-2.32]
2	0.95	4.24	29.3 %	0.09	0.08	-0.01	-0.4	-0.37	-0.029	-2.64
				[1.64]	[1.47]	[-0.09]				[-2.76]
3	0.96	4.21	30.4 %	0.09	0.07	0.01	0.04	0.08	-0.011	-1.42
				[1.54]	[1.44]	[0.19]				[-2.16]
4	0.92	4.72	22.4 %	-0.01	-0.03	-0.01	0.5	0.58	0.011	3.19
				[-0.19]	[-0.40]	[-0.19]				[4.35]
5	0.51	6.6	7.5 %	-0.61	-0.54	-0.23	1.93	2.08	0.063	11.05
				[-3.92]	[-3.70]	[-1.81]				[5.30]
5-1	-0.58			-0.69	-0.65	-0.37				
	[-2.90]			[-3.25]	[-2.98]	[-1.64]				
Joint test p-value				0.00	0.00	0.34				0.00

5.2.1 Properties of the FVXO Factor: 1986 - 2018

Again, FVXO needs to be seen in the context of established risk-factors. Table 5.5 displays the contemporaneous correlation between FVXO and ΔVXO at the daily frequency in panel A and with the FF-5 factors plus LIQ and UMD in panel B. Additionally, the left side contains their means and standard deviations at the respective frequency.

Table A is very similar to its counterpart over the shorter period. ΔVXO has the zero-mean that is to be expected and a low standard deviation slightly above 2. FVXO replicates both closely. The connection between both is further underlined by a 91% correlation. At the monthly frequency a few things have changed. The mean of ΔVXO has halved while its std dev has increased slightly. With 0.17, the mean of FVXO is less than a third of its former 0.66, while the standard deviation has decreased by about 25% to 8.79. At the same time, their monthly covariance decreased from 0.7 to 0.57.

In panel B, ΔVXO is merely given for comparison as FVXO was constructed for the exact purpose of increased performance at this frequency. The contemporaneous correlations between FVXO and MKT, SMB and CMA stayed largely constant at around -0.67, -0.14 and 0.26 respectively. In contrast, the correlation with HML almost halved from 0.24 to 0.15, the correlation with LIQ decreased slightly in magnitude from -0.48 to -0.34 and the correlation with RMW more than doubled from 0.07 to 0.18. Most remarkably, the correlation with UMD, the momentum factor, went from -0.26 over 1986 to 2000 to -0.01 over 1986 to 2018. The higher absolute correlations with RMW and CMA in comparison to SMB and HML are consistent with the considerable decrease in pricing errors when including the two former into a model explaining the quintile portfolios monthly returns (see table 5.4 columns V to VII).

The broad picture from subsection 5.1.1 remains intact. FVXO seems to share most information with the market factor and the Pástor and Stambaugh (2003) liquidity factor, which are probably related as Liquidity tends to try up (making LIQ rise) when market returns are negative. None of the correlations at the monthly frequency are high enough to justify fears FVXO might be a redundant factor.

5.2.2 ΔVXO Robustness Tests: 1986 - 2018

Applying the double-sorting procedure with respect to momentum and $\beta_{\Delta VXO}$ that was described for the AHXZ period of 1986 to 2000 in subsection 5.1.2 to the longer sample of 1986-2018 yields very similar results. These are reported in table 5.6.

TABLE 5.5: **Factor Correlations: VXO 1986 - 2018**

On the left side, the mean and standard deviation of both the first-difference of the VXO and of the FVXO factor are given at the daily (top) and monthly (bottom) frequency. On the right side, their contemporaneous correlations with each other are given at the daily (panel A) and monthly (panel B) frequency . In addition, panel B contains correlations with common cross-sectional risk-factors. MKT, SMB and HML were proposed in Fama and French (1993). CMA and RMW were proposed in Fama and French (2015). UMD was constructed by Ken French. All 7 can be found on his website. LIQ was proposed in Pástor and Stambaugh (2003) and can be found on Robert Stambaugh's website.

			Panel A: Daily Correlations								
	Mean	Std dev	FVXO	Δ VXO							
Δ VXO	0.00	2.27	0.91	1.00							
FVXO	0.01	2.11	1.00	0.91							
			Panel B: Monthly Correlations								
			FVXO	Δ VXO	MKT	SMB	HML	UMD	LIQ	RMW	CMA
Δ VXO	0.03	5.09	0.57	1.00	-0.58	-0.20	0.06	0.18	-0.08	0.23	0.20
FVXO	0.17	8.79	1.00	0.57	-0.69	-0.15	0.15	-0.01	-0.34	0.18	0.24

Table 5.6 shows that controlling for the previous 12-month return lowers the average returns of all five portfolios, but leaves the pattern across average returns, as well as the significantly negative return on the 5-1 portfolio, intact. The *Pre-Formation* $\beta_{\Delta VXO}$ remain satisfactorily close to their previous values, while the *Next Month Post-Formation* β_{FVXO} change noticeably, but roughly retain the necessary decline from rank 1 to 5, thus giving meaning to the pricing errors.

The changes in pricing errors when controlling for momentum relative to not controlling for momentum over the period of 1986 to 2018 are very close to the respective changes over the period of 1986 to 2000. Again, the largely monotone decline in pricing-model-intercepts from rank 1 to 5 disappears after controlling for momentum. Instead, intercepts increase from 1 to 3 and decrease from 3 to 5. Yet, the 3 to 5 decline is sufficiently steep to make the 5-1 portfolio retain its significantly negative intercept with respect to all three models. Controlling for momentum even pushes the 5-1 portfolio's FF-5 intercept into significant territory, while this intercept was found not to be significant without controlling for momentum.

Thus, as can be expected for an anomaly as robust as momentum, momentum effects affect the results obtained via the AHXZ procedure over 1986 to 2018. In particular, the monotone decrease in pricing errors reported in table 5.4 must be interpreted with caution as it was shown to disappear when momentum effects are controlled for. Yet, the central results remain intact. Stocks with a high (low) exposure to innovations in uncertainty did historically earn much lower (higher) average returns both before and after controlling for momentum.

TABLE 5.6: **ΔVXO in the Cross-Section of Stock returns: 1986 - 2018, controlling for Momentum**

For each month from January 1986 to December 2018 the daily returns of all NYSE, NASDAQ and AMEX stocks are regressed on MKT and ΔVXO. Each month, the stocks are divided into five portfolios depending on their return over the previous 12 months and within each of these fifth further divided depending on their $\beta^i_{\Delta VXO}$. Finally, the lowest $\beta^i_{\Delta VXO}$ portfolio from each past-return portfolio are combined into a portfolio of rank 1, the second lowest into rank 2 and so forth. Returns are value-weighted within each portfolio. Column II reports the average and column III the standard deviation of the 179 monthly total (not excess) returns for each portfolio. Columns IV to VI contain the intercepts in monthly regressions of the portfolio returns on the market return, the FF-3 factors and the FF-5 factors, respectively. Column VII reports the time-series average of equal-weighted monthly averages of $\beta^i_{\Delta VXO}$ of consitituent stocks for each portfolio. The last column reports the $\beta^i_{\Delta FVXO}$ coefficients in the regression of monthly portfolio returns over the whole sample on a constant, the FF-3 factors and the FVXO factor. FVXO is the daily factor constructed by monthly rebalancing the 5 portfolios so as to match daily innovations in the VXO as closely as possible. Square brackets contain robust Newey-West t-statistics. The *joint-test p-values* are based on an F-test by Gibbons, Ross, and Shanken (1989).

						Factor Loadings	
Rank	Mean	Std. Dev.	CAPM Alpha	FF-3 Alpha	FF-5 Alpha	Pre-Form $\beta\Delta$ VXO	Next Month Post-Form β FVXO
1	0.89	6.87	-0.16	-0.16	-0.1	-1.74	1.79
			[-1.25]	[-1.39]	[-0.74]		[1.29]
2	0.92	5.78	-0.03	-0.07	-0.06	-0.42	1.49
			[-0.45]	[-0.89]	[-0.78]		[1.20]
3	0.95	5.83	0.00	-0.04	-0.01	0.04	2.56
			[0.00]	[-0.57]	[-0.13]		[1.70]
4	0.83	6.10	-0.15	-0.19	-0.13	0.52	6.81
			[-1.64]	[-2.25]	[-1.23]		[4.85]
5	0.39	7.18	-0.71	-0.70	-0.47	1.86	10.14
			[-4.83]	[-5.08]	[-3.17]		[5.3]
5-1	-0.5		-0.55	-0.54	-0.37		
	[-3.28]		[-3.35]	[-3.18]	[-2.3]		
Joint test p-value			0.00	0.00	0.01		0.00

5.3 The Pricing of Uncertainty-Risk over Time

In the sections above, portfolio 5-1 was discussed frequently. 5-1 is the zero-cost portfolio that each month is long (short) the quintile of stocks with the highest (lowest) covariance with ΔVXO over the past month. Since the 5-1 portfolio is constructed by buying and selling the same value of stocks in dollar terms each month, it should earn a mean 0 return (minus trading costs) if the stocks it buys and sells have the same expected returns.

Section 5.1 showed that, over the sample of 1986 - 2000, the hypothesis that the stocks 5-1 buys and those it sells have the same expected returns can be rejected at the 1% significance level. The 5-1 portfolio earned an excess return of -1.05% per month over that period, which is a very impressive difference. Section 5.2 demonstrated the same rejection at the 1% level over 1986 - 2018, though with a lower t-statistic of -2.90 instead of -3.97 and almost halve the mean excess return of -0.58 % per month.

For the question of this thesis, whether uncertainty-risk is priced in the cross-section of stock returns, these developments are crucial. In order to have more than just the AHXZ period and my period as samples, table 5.1 illustrates the development of 5-1's average return since February 1986 over an increasing window. That is, the black line above the year 1995 constitutes the average of monthly returns of the 5-1 zero-cost portfolio from February 1986 to January 1995. The next point on the black line shows the average of monthly returns of the 5-1 portfolio from February 1986 to February 1995 and so on.

I have chosen this window to start only in January 1990 to make sure there are enough monthly observations to estimate portfolio 5-1's expected return with some precision. The grey area around the black line presents a 2 standard deviation significance interval around the means. Finally, I have used red squares to highlight significant events. They are labeled with the fundamental event, their exact month and the value of the black line during that month. See below for why only one square carries a *fundamental event* label.

The interpretation of the 5-1 portfolios past average return (i.e. of the black line) has to occur with great caution. It's value is influenced by (I) the dispersion of stock's exposure to uncertainty risk (II) the development of uncertainty risk over time (III) the uncertainty risk premium and last, but not least, by (IV) random shocks. If there is a higher dispersion in stock's exposure to uncertainty risk, that is, if stocks in portfolio 5 have higher $\beta^i_{\Delta VXO}$ (from equation 5.1) relative to those of portfolio 1, the difference in expected returns should be higher, thus increasing the absolute value of the 5-1 return. However, the stocks' theoretical exposure to uncertainty-risk does not matter if there is no variation in VXO. Also, some movements of the black line in table 5.1 are definitely random and have no relevance for the uncertainty-risk factor. Due to all these confounding factors, I try to be as cautious in the interpretation of table 5.1 as possible.

On the most general level, periods over which the black line sinks are periods over which 5-1's monthly return is below its previous average, thus reducing the new average. Such a period is shown in table 5.1 to sustainably exist over the considered period only from January 1990 to the first red square (counted from the left). This square represents December 2000, the end of the period looked at in the original study of AHXZ. The average return of -1.05 matches the one reported in table 5.1. While this must be so, it is good to have these occasional, natural tests of consistency. Similarly, the fifth square represents the end of the period looked at in this thesis and its average return matches the one reported in table 5.4.

Over the 5 years after the first red square, the 5-1 return lies at its mean. During the months immediately preceding the second red square, the 5-1 return lies markedly above its mean, as the black line rises steeply. This second square represents the publication of AHXZ in the Journal of Finance. It should be differentiated from the other four squares as it is the only event that might reasonably have had an influence on the pricing of uncertainty risk. This is explained in the next paragraph.

McLean and Pontiff (2016) re-examine 97 factors that have been reported in academic journals as predicting parts of the variation in average returns between stocks. They apply a procedure very similar to the one considered here, going long (short) the quintile of stocks with a high (low) exposure to each factor. On average, they find a 58% reduction in average returns of these zero-cost portfolios post-publication relative to the pre-publication period. Of these 58%, they attribute 26% to data snooping (i.e. reduced out-of-sample factor performance) and the remaining 32% to investors trading on the newly published factor and arbitraging away the excess returns.[11]

The pattern found in my figure 5.1 is in accordance with their findings. The publication of AHXZ marks a break in the solid line, after which the 5-1 returns generally lie above their previous mean. The ascent of the 5-1 mean-return from -0.97 during the AHXZ-publication-month to -0.58 at the end of my study in December 2018, is broken only by one short, steep decline. I have marked its beginning and

[11] This conclusion is consistent with their observation that factors' 5-1 average returns decline by less if their extreme quintile portfolios show high idiosyncratic risk or low liquidity, that is, if the factor is difficult to arbitrage.

end with squares three and four. The timing and duration of the change in direction of the black line suggests a connection to the financial crisis.

However, this long period of absolute returns on the 5-1 portfolio above their past means and thus of decreasing support for a priced uncertainty risk factor, does not begin with the publication of AHXZ. The minimum of the black line is found to coincide with October 2002 and the steep rise begins in April 2005. Ang Hodrick Xing Zhang published a working paper on uncertainty-risk in October 2004, which might have informed investors about the high returns of an uncertainty-risk based trading strategy, but McLean and Pontiff (2016) find working papers (in contrast to academic journal articles) to generally have only a limited influence on factor performance.

In any case, the consistently worse performance of the uncertainty-risk factor after its publication, and in fact the break from general improvement in performance to general deterioration in performance being close to that publication, raises considerable doubts whether uncertainty-risk is systematic. A *systematic* risk influences average returns because investors do not want to bear it. They consciously accept low returns on stocks that allow them to avoid said risk. High returns on stocks that increase their exposure to the risk do not constitute arbitrage opportunities for them. Consequently, the publication of a systematic risk factor should not influence its pricing.

On the other hand, a mispricing that has eluded investors attention would disappear with its publication as it is arbitraged away. Also, the authors of a factors publication might be guilty of data mining. In that case the factor can be expected to disappear post-publication, too. For our understanding of investor preferences and financial markets only systematic risk factors are of interest.

With respect to uncertainty risk being such a systematic factor, the V-shaped form of the 5-1 portfolio's average returns with the factor's publication near the minimum is not encouraging. However, the rise in past average returns from 2005 onwards is rather slow, indicating that the monthly 5-1 returns are not much above their past means. If uncertainty-risk is not a systematic risk factor and AHXZ merely made investors aware of a profitable trading strategy, they would have traded on the new factor and pushed 5-1 monthly returns close to zero. Thus, I would expect a much steeper rise in the black line post-publication.

In conclusion, the support for a systematic uncertainty-risk factor is weaker post-publication, but the speed with which 5-1's average returns rise post-publication is not sufficient to definitely reject a systematic risk-factor explanation.

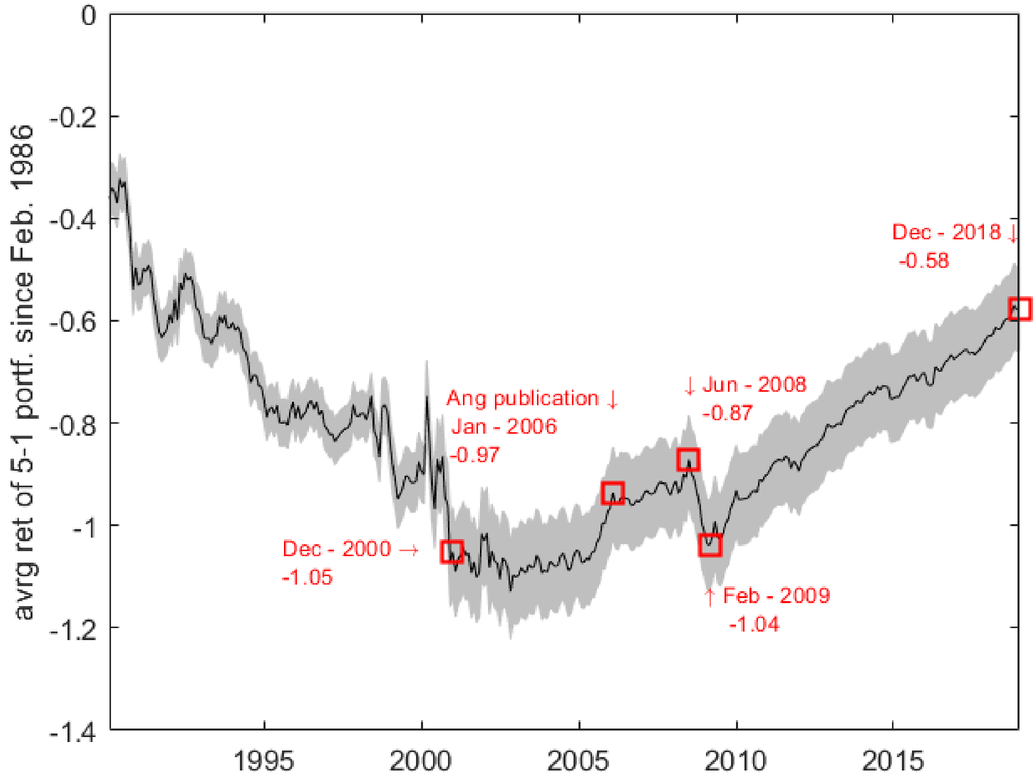

FIGURE 5.1: **Average returns of a zero-cost uncertainty-risk portfolio**

This figure shows the average of past monthly returns over an increasing window for the 5-1 zero-cost portfolio that is long (short) stocks with high (low) exposure to innovations in the VXO index. The grey area gives a two standard deviation significance interval around these means. Red squares highlight significant dates and are labeled.

Chapter 6

Uncertainty Risk: TYVIX

Chapter 5 explained the methodology of Ang et al. (2006), who use the first-difference of the VXO implied volatility index to proxy for changes in uncertainty and uncover a systematic uncertainty-risk factor in the cross-section of stock returns. Section 5.1 applied the AHXZ methodology to the period of 1986 to 2000, thus replicating their results. Subsequently, section 5.2 updated the study to 1986 to 2018, showing that the empirical support for an uncertainty-risk factor has weakened but not altogether disappeared.

However, there is nothing inherent in the uncertainty-risk factor's theoretical motivation (given in section 4.1) that would make VXO its optimal proxy. To show uncertainty-risk from a new angle, this chapter changes the proxy variable to the *TYVIX implied treasury volatility index*, shortens the period considered to 2009 to 2018 and restricts the view to banking stocks.

These choices are motivated by the hypothesis that government bailouts of financial institutions in the US during the crisis of 2007/08 might have led investors to prefer exposure to interest-rate-uncertainty, as they expect to be rescued in case of an impending default. Thus, the patterns across average returns and pricing errors should lie opposite to those found for VXO among all stocks in the previous chapter. Finding such a reversed effect in a situation where that makes intuitive sense could constitute strong support for the potential of an uncertainty-risk factor in the cross-section, independent from the specific proxy.

In this chapter, section 6.1 applies the usual AHXZ procedure and finds some empirical support for the hypothesis above, but also hints at methodological problems. Subsection 6.1.1 shows the new interest-rate-uncertainty-risk factor to be largely orthogonal to established risk-factors. Subsection 6.1.2 shows that the results of this chapter are robust against the simultaneous consideration of a size-effect.

To the best of my knowledge, there is no published study on the TYVIX index in the cross-section of stock returns yet. Therefore, this chapter provides a completely new perspective on uncertainty-risk.

6.1 TYVIX in the Cross-Section of Bank-Returns: 2009 - 2018

In this section, the methodology of AHXZ is applied to the returns of banking stocks over the period of 2009 - 2018. Crucially, this section uses the TYVIX implied-treasury-volatility index instead of the VXO implied-equity-volatility index as a proxy for uncertainty risk. There are several motivations for this different approach to uncertainty risk.

First, there is nothing inherent in the theoretical motivation of an uncertainty-risk factor that would make VXO an optimal proxy. Since, the VXO is derived from options on the S&P 100 equity index and the TYVIX from options on treasury-note futures, they capture different aspects of uncertainty by design. This difference in dimensions to uncertainty is highlighted by a mere 57% correlation between VXO and TYVIX and a mere 12% correlation between their first-differences. In particular, the TYVIX is designed to covary strongly with innovations in US interest-rate uncertainty (see section 4.4 for both indices). Intuitively, the level of interest rates has an outsized influence on banks (and insurance companies). Thus, innovations in the TYVIX might capture an aspect of uncertainty that is priced only for banking (and insurance) stocks.

Also, Lewellen, Nagel, and Shanken (2010) name the testing of asset pricing models among industry-subsets as one of their suggestions on how to avoid the current flood of seemingly significant cross-sectional factors. TYVIX among post-crisis banking stocks is a good opportunity to do so.

Most importantly, Gandhi and Lustig (2015) find a new *size* risk-factor among post-crisis banking stocks, that explains the significantly higher risk-adjusted average returns of small bank stocks and is orthogonal to other common risk-factor (including the FF size factor SMB). They explain this new size factor with investors' experiences of government bailouts for large financial institutions, while small banks were usually not rescued from bankruptcy.

In the same sense, it is possible that investors are seeking exposure to interest-rate uncertainty when investing in bank stocks since the crisis. If they expect to be rescued only in states of monetary crisis where interest-rate uncertainty increases markedly and only for investments in banking-stocks, it could be rational to demand higher average returns on stocks that hedge against interest-rate uncertainty. However, these theoretical considerations remain hypotheses and conjectures. A more extensive study might develop an equilibrium-model to validate or reject them.

Chapter 5 has shown some support for an uncertainty-risk factor, though not overwhelming and continuously weakening since the early 2000s. Finding a reversal of the effect where that intuitively makes sense would be strong support for an uncertainty-risk factor, independent of the specific proxy variable. The issue of different possible proxies for uncertainty risk is addressed theoretically in 4.1 and empirically in 4.4.

Again, I will not go into the details of the AHXZ procedure in this section, as those details are explained in section 5.1. Instead, this section focuses on differences in methodology and the interpretation of results. The most important difference in procedure is the use of TYVIX instead of VXO. Again, I want to obtain return covariances with *unexpected changes* in uncertainty, to estimate in how far a stock can function as a hedge against those. And again, the high persistence of the index (see figure 4.2) makes a simple first difference of the TYVIX the more robust alternative in comparison to a model for its conditional mean. In the following, these first-differences will be denoted $\Delta TYVIX$.

The CRSP daily stock file is the basis for the analysis. As is standard in the asset pricing literature *banking stocks* are defined via the FF-conversion of CRSP SIC codes into 49 industries. Industry 45 constitutes banking and 46 insurance, which I use in a few robustness tests. Over the period of January 2009 to December 2018 the CRSP daily file contains between 553 and 321 such banking stocks simultaneously and 651 different banks in total.

The post-crisis period was chosen to begin with January 2009 as I wanted to consider only full years to exclude potential seasonality effects and January 2008 would have been too early. The period was chosen to end with December 2018 as I wanted to have as many data as possible to estimate relevant coefficients precisely. In chapter 5 the availability of VXO only from January 1986 onwards restricted the monthly rebalanced quintile portfolios to start in February. Beginning the analysis in January 2009 has the advantage that TYVIX data during December 2008 allow quintile portfolio returns to actually start in January 2009. Thus, this analysis has 120 monthly returns.

Over these 120 months, banking stocks are monthly re-sorted into 5 *quintile* portfolios depending on their past-month $\beta^i_{\Delta TYVIX}$ from equation 5.1 (just using TYVIX instead of VXO) from low betas (portfolio 1) to high betas (portfolio 5). The time-series average of these value-weighted portfolios is reported in column II of table 6.1. Portfolios 2 to 5 show a clear, monotone increase in average returns from low to high treasury-uncertainty-risk exposure. This is consistent with the theoretical motivation for a reversed uncertainty effect among banking stocks, given above. If investors want to take on interest-rate uncertainty-risk because they expect to be rescued, a portfolio with high (low) covariance with changes in treasury-uncertainty should earn higher (lower) average returns as it would constitute (not constitute) an unwanted hedge. This is exactly what is found here from portfolio 2 to 5.

Only portfolio 1 destroys the picture, with average returns above those of 2,3 and 4, though below those of portfolio 5, leading to the expected positive return on the 5-1 *zero-cost* portfolio. However, with 0.36% per month the 5-1 average returns are relatively modest and, with a robust Newey-West t-statistic of 0.89, they are not different from zero at any common significance level.

The high returns on portfolio 1 are made more troubling by the regular pattern in the first *Factor Loadings* column, which for each portfolio shows the time-series average of monthly averages of constituent stocks' $\beta^i_{\Delta TYVIX}$. The monotone increase from portfolio 1 to 5 shows that the monthly rebalancing worked. On average, stocks with a high (low) covariance with $\beta^i_{\Delta TYVIX}$ tended to be sorted into portfolio 5 (1). Thus, the relatively high average returns of portfolio 1 are not the result of mis-sorting.

They also do not seem to be the result of changing treasury-uncertainty betas pre- and post-formation. The second-to-last column of table 6.1 contains average stock betas during the month post-formation and, though there is no monotone increase from portfolio 1 to 5 and the average of betas is generally disappointingly low, at least the portfolio 1 average is far below those of portfolios 2 to 4. If the reversed uncertainty-effect explanations from above were correct, this lower average of $\beta^i_{\Delta TYVIX}$ should go along with lower average returns. Column II has shown that this is not the case.

However, so far regression 5.1 has only controlled for market-risk while estimating $\beta^i_{\Delta TYVIX}$. Thus, there might be a lot of omitted variable-bias in their estimation. The consideration of pricing errors of common factor models when confronted with the quintile portfolios' returns to some degree alleviates this problem. These pricing errors are remarkable. They are reported in columns V to VII in table 6.1. The average return on portfolio 1 is 0.9% per month. The CAPM predicts this average return to lie at 1.77%, thus -0.87% remain unexplained. All five quintile portfolios underperform the CAPM expectation in this way, which might be explained by the generally low returns on banking stocks since the financial crisis.

As explained above, if the motivation for a positive price of treasury-uncertainty-risk among post-crisis banking stocks is correct, portfolio 1 (5) should have relatively low (high) average returns. This should be robust to the inclusion of other risk-factors. Thus, portfolio 1 should underperform the expectations of the CAPM, FF-3 and FF-5 relatively more than portfolio 5 and the pattern between them should optimally be monotone. However, there is no reason to have expectations regarding the absolute values of pricing errors. As a result, the almost monotone increase in CAPM pricing errors from portfolio 1 to 5 supports the hypothesis of this chapter. On the other hand, the return on the 5-1 portfolio is not significantly different from zero and even the hypothesis of all intercepts being jointly zero cannot be rejected.[1]

Those relationships remain largely the same when considering the FF-3 model, i.e. when adding SMB and HML to the MKT. Portfolio 2 shows a lower pricing error than portfolio 1, breaking an otherwise monotone increase from 1 to 5. The 5-1 return is not significant and the p-value is very high. Yet, the intercepts are generally closer to zero, with portfolio 5 even having a positive intercept (the FF-3 model predicts a lower average return for portfolio 5 than is realized). Thus, SMB and HML seem to add much explanatory power to the model.

CMA and RMW explain a further significant portion of the quintile portfolios' returns, reducing the intercepts of 1,3 and 4 to basically zero, with 2 being a negative- and 5 a positive outlier. The 5-1 return is not significant and the joint test p-value is huge.

Across columns V, VI and VII, there is definitely something worth discussing here. The expected pattern from portfolio 1 to 5 is found for the CAPM and FF-3 pricing errors and even though it disappears for the FF-5 model, the 5-1 return is remarkably consistent across all three. However, the universal lack of statistical significance prevents a positive conclusion regarding a priced interest-rate-uncertainty-risk factor in the cross-section of post-crisis bank stocks.

Additionally, it has been discussed in chapter 5 that columns V to VII report *monthly* alphas across the whole sample, which necessitates an investigation into the quintile portfolios' exposure to uncertainty-risk at the same frequency and over the same sample. In that respect, the results reported in table 6.1 significantly weaken the encouraging evidence from columns V to VII.

[1] The high p-value on the joint hypothesis test seems surprising, given the generally high absolute intercepts. However, CAPM, FF-3 and FF-5 perform horribly when confronted with the 5 quintile portfolios, leading to very high standard deviations of the intercept estimates. This explains the high p-values, as well as the low t-statistics, in columns V to VII.

The quintile portfolios are monthly rebalanced into the factor mimicking portfolio *FTYVIX* so as to make the FTYVIX returns match daily $\Delta TYVIX$ over each month as closely as possible. The similarity of columns *Pre-Form* β_{FTYVIX} and its left neighbor indicates that stocks generally have a similar exposure to *FTYVIX* and $\Delta TYVIX$. Thus, building a mimicking-portfolio seems to have succeeded, though not to the degree of tables 5.1 and 5.4, where the two columns are almost identical.

This is not surprising. Restricting the sample to post-crisis banking stocks excludes more than 95% of companies from the analysis. Thus, the quintile portfolios now consist of far less individual stocks, which potentially introduces a lot of noise into the portfolios' returns. This is consistent with the decidedly higher portfolio return standard deviations (column III) relative to earlier tables.[2]

More important than these small daily deviations, the coefficients on monthly *FTYVIX* returns in regressions of monthly quintile portfolio returns onto an intercept, the FF-3 factors and FTYVIX over January 2009 to December 2018 (last column of table 6.1) are very far from their intended values.

At the start of this analysis, stocks were re-sorted into five portfolios every month depending on their exposure to innovations in interest-rate-uncertainty-risk, in order to produce five traded assets that have a consistently different, increasing exposure to this risk. The *Next Month Post-Form* β_{FTYVIX} column shows a complete failure to do so. Portfolio 1 has the highest covariance with FTYVIX and portfolio 5 has the lowest covariance while 2,3 and 4 exhibit no clear pattern between them. This is almost the opposite of what was intended. At least none of the betas is significant, though jointly they are.

As mentioned above, the last column is especially problematic for the interpretation of CAPM, FF-3 and FF-5 alphas. Finding relatively lower (more negative) pricing errors towards portfolio 1 and relatively higher pricing errors towards portfolio 5 was a positive sign for the investigated risk-story only under the assumption that the former tended to have a relatively lower covariance with innovations in interest-rate-uncertainty-risk. This assumptions seems to have been incorrect.

In conclusion, the search for a positive price of uncertainty-risk among post-crisis banking stocks did not only yield any significant supportive evidence. However, the method of investigation does not seem to have been appropriate for a small number of stocks. The encouraging patterns in average returns and pricing errors might become significant when a more suitable method is applied.

[2] For a three portfolio analysis see subsection 6.1.1. Here, I decided to stick with 5 portfolios in order to make a comparison with chapter 5 as simple as possible.

Finally, it should be noted that the restriction to post-crisis banking stocks in this chapter had a significant influence on results. I examined the performance of $\Delta TYVIX$ among all stocks over 1986 - 2018 and found a completely different pattern across quintile portfolio means and alphas: low returns on the extreme portfolios and essentially uniform portfolios 2,3 and 4. To spare the reader a fourth interpretation of the same table, I have confined *TYVIX 1986 - 2018* to the appendix.

TABLE 6.1: **ΔTYVIX in the Cross-Section of Banking returns: 2009 - 2018**

For each month from January 2009 to December 2018 the daily returns of all Banking stocks listed on the NYSE, NASDAQ and AMEX are regressed on MKT and $\Delta TYVIX$. The stocks are then divided into 5 portfolios from lowest $\beta^i_{\Delta TYVIX}$ (portfolio 1) to highest $\beta^i_{\Delta TYVIX}$ (portfolio 5). Thus, the 5 portfolios are rebalanced at the end of each month. Their monthly returns are given as the value-weighted average of their current constituents. Column II reports the average and column III the standard deviation of the 120 monthly total (not excess) returns for each portfolio, as well as a zero-cost portfolio that goes long portfolio 5 and short portfolio 1. Column IV gives their average market share. Columns V to VII contain the intercepts in monthly regressions of the portfolio returns on the market return, the FF-3 factors and the FF-5 factors, respectively. They can be interpreted as pricing errors of the respective model. Column 1 under the sub-heading *Factor Loadings* reports the time-series average of equal-weighted monthly averages of $\beta^i_{\Delta TYVIX}$ of consitituent stocks for each portfolio. The third-to-last column gives the same for $\beta^i_{\Delta FTYVIX}$, with FTYVIX being the daily factor constructed by monthly rebalancing the 5 portfolios so as to match daily innovations in the TYVIX as closely as possible. In contrast to the two preceding columns, the second-to-last column reports the time-series average of the monthly $\beta^i_{\Delta TYVIX}$ of the portfolios directly, while controlling for the market factor. The last column reports the $\beta^i_{\Delta FTYVIX}$ coefficients in the regression of monthly portfolio returns over the whole sample on a constant, the FF-3 factors and the FTYVIX factor. Square brackets contain robust Newey-West t-statistics. The *joint-test p-values* are based on an F-test by Gibbons, Ross, and Shanken (1989).

							Factor Loadings			
I Rank	II Mean	III Std. Dev.	IV % Mkt Share	V CAPM Alpha	VI FF-3 Alpha	VII FF-5 Alpha	Pre-Formation $\beta\Delta$ TYVIX	Pre-Form β FTYVIX	Next Month Post-Form $\beta\Delta$ TYVIX	Next Month Post-Form β FTYVIX
1	0.90	8.08	12.9%	-0.87	-0.36	-0.05	-3.07	-3.38	0.01	-11.05
				[-1.97]	[-1.19]	[-0.17]				[-0.23]
2	0.48	6.76	22.6%	-0.98	-0.56	-0.35	-0.73	-1.36	0.069	-97.14
				[-2.33]	[-1.74]	[-1.26]				[-1.52]
3	0.74	6.4	27.9%	-0.68	-0.22	-0.09	0.08	-0.47	0.131	-36.94
				[-1.58]	[-0.79]	[-0.31]				[-0.84]
4	0.83	6.16	24.4%	-0.56	-0.20	0.00	0.85	0.48	0.127	-36.97
				[-1.62]	[-0.68]	[0.01]				[-1.05]
5	1.26	7.48	12.2%	-0.28	0.12	0.39	2.97	2.65	0.056	-154.46
				[-0.62]	[0.38]	[1.43]				[-1.46]
5-1	0.36			0.59	0.49	0.45				
	[0.89]			[1.36]	[1.09]	[1.12]				
Joint test p-value				0.24	0.58	0.73				0.00

6.1.1 Properties of the TYVIX Factor among Bank-Returns: 2009 - 2018

Above, the unexpected covariances between monthly quintile portfolio returns and the FTYVIX factor constituted a major objection to the validity of the AHXZ-procedure for a small subset of stocks over a comparatively short period of time. This subsection provides a closer look at the FTYVIX factor and its relation to other common risk-factors. To that end, panel A of table 6.2 shows daily means, standard deviations and correlations for $\Delta TYVIX$ and FTYVIX. Panel B contains corresponding figures for $\Delta TYVIX$,FTYVIX, the FF-5 factors, UMD and LIQ on a monthly basis.

On the positive side, the zero-mean of TYVIX's first-difference shows that I was justified in interpreting deviations from its unconditional mean as unexpected changes instead of specifying a conditional mean. On the negative side, the very low daily $\Delta TYVIX$ standard deviation of 0.35 signifies little variation that could influence the cross-section of returns. Yet, this probably did not cause the problems in factor replication as the first *Factor Loadings* column in table 6.1 displays reasonable and sufficiently disperse covariances of bank stock returns with $\Delta TYVIX$.

The 58% correlation of $\Delta TYVIX$ with its factor-mimicking portfolio (FTYVIX) suggests that this mimicking was much less successful than for VXO in chapter 5, where the corresponding correlation reached 91%. This is not surprising, since there are much less stocks in this chapter, thus introducing more noise that confounds an exact replication of $\Delta TYVIX$ via returns.

On a monthly basis the FTYVIX factor has a low mean and low standard deviation, indicating that the less-then-perfect construction of FTYVIX on a daily frequency might have translated into little informational content on a monthly frequency. This might explain the oscillating and non-significant FTYVIX betas in the last column of table 6.1.

The monthly correlations of FTYVIX with all common risk factors are remarkably low. This indicates the discovery of a new risk-factor that is orthogonal to previously reported risk-dimensions. The low correlations are probably not due to the problems in constructing FTYVIX mentioned above, since they are equally found for $\Delta TYVIX$.

In conclusion, interest-rate uncertainty-risk seems to be remarkably independent from common risk-dimensions, but the method of constructing an associated replicating-portfolio used in this thesis is probably not optimal.[3]

[3] This suspicion is strengthened by the last column of table A.1. Using more stocks over a longer period leads to lower quintile portfolio standard deviations and full sample uncertainty-risk exposures that are more in line with what I tried to construct, though the last column still does not contain a monotone increase.

TABLE 6.2: **Factor Correlations: TYVIX Banking 2009 - 2018**

On the left side, the mean and standard deviation of both the first-difference of the TYVIX and of the FTYVIX factor are given at the daily (top) and monthly (bottom) frequency. On the right side, their contemporaneous correlations with each other are given at the daily (panel A) and monthly (panel B) frequency . In addition, panel B contains correlations with common cross-sectional risk-factors. MKT, SMB and HML were proposed in Fama and French (1993). CMA and RMW were proposed in Fama and French (2015). UMD was constructed by Ken French. All 7 can be found on his website. LIQ was proposed in Pástor and Stambaugh (2003) and can be found on Robert Stambaugh's website.

			Panel A: Daily Correlations								
	Mean	Std dev	FTYVIX	Δ TYVIX							
Δ TYVIX	0.00	0.35	0.58	1.00							
FTYVIX	0.00	0.21	1.00	0.58							
			Panel B: Monthly Correlations								
			FTYVIX	Δ TYVIX	MKT	SMB	HML	UMD	LIQ	RMW	CMA
Δ TYVIX	-0.08	0.98	0.31	1.00	-0.14	0.07	0.07	-0.11	0.07	0.02	0.01
FTYVIX	0.05	0.85	1.00	0.31	-0.24	0.01	-0.04	-0.11	0.1	0.13	-0.02

6.1.2 TYVIX among Bank-Returns, controlling for size

This whole chapter was inspired by the paper of Gandhi and Lustig (2015). They found a new, orthogonal size-effect among post-crisis US banking stocks and argued this might be due to the US government bailing out large, but not small, financial institutions in case of an impending default.

In this subsection I control for banks' size while examining the effects of interest-rate uncertainty-risk exposure on average returns. This way, I want to find out whether the results of Gandhi and Lustig (2015) can explain the supportive (though non-significant) pattern in quintile portfolio average returns presented in section 6.1.

To that end, I perform the double-sorting procedure first explained in subsection 5.1.2. Notable differences are that (I) I am controlling for a firm's market capitalization instead of momentum and (II), due to the significantly lower number of stocks, I sort into 3-by-3 portfolios instead of 5-by-5. That is, at the end of each month from January 2009 to December 2018 I sort all bank stocks in the CRSP daily file into three portfolios, depending on their current market capitalization. The CRSP daily file contains closing share prices and the number of shares outstanding, thus enabling an easy calculation of a stock's market capitalization via multiplication of the two.[4] Subsequently, I further divide each of these thirds into portfolios of

[4] Gandhi and Lustig (2015) use book-values to uncover their size factor. Therefore, I would have been a better control for their results had I double-sorted by firms' book values, instead of their market capitalization.

stocks with high, medium and low daily covariance with $\Delta TYVIX$ over the past month. Thus, I obtain 9 portfolios for each month. Linking, for example, all portfolios with high market capitalizations and high $\beta_{\Delta TYVIX}$ over time, allows for the calculation of average returns over the whole sample. Again, the stocks' returns are value weighted within each portfolio.

The double-sorting procedure should prevent the lower risk-adjusted average returns of large bank stocks from confounding my analysis, since I can compare three portfolios with different $\beta_{\Delta TYVIX}$ that are all low (medium or large)-cap. Table 6.3 reports the nine portfolios' monthly average returns, their standard deviations (in round brackets) and their market betas (in triangular brackets). The portfolios in the right column, combine the respective three portfolios to the left. That is, in effect the right column reports results as if I had not controlled for size, but simply executed the usual AHXZ sorting into three, instead of five, portfolios.

The clear, monotone increase in average returns from low to high $\beta_{\Delta TYVIX}$ in the right column of table 6.3 is in accordance with the hypothesis of a positive price of interest-rate-uncertainty risk among post-crisis banking stocks. This pattern is found among all stocks (right column), among high market-cap stocks (left column) and among middle market-cap stocks. Only among small caps, medium $\beta_{\Delta TYVIX}$ stocks outperform the extremes. Importantly, these increase in average returns from row 3 to 1 cannot be explained by a either higher standard deviations of returns or by higher market betas, as both tend to increase in the opposite direction.

Thus, the 3-by-3 double sorting procedure summarized in table 6.3 suggests a priced interest-rate-uncertainty-risk factor in the cross-section of post-crisis US bank stock returns. This factor is robust against the size-effect. Whether it can be shown to be significant and whether it is robust against other cross-sectional risk-factors remains for subsequent studies.

Finally, it is noteworthy that I find the usual size effect of higher average returns for small stocks. The bottom row is a combination of the respective three portfolios above. That is, in effect it reports results as if I had only controlled for size, not for $\beta_{\Delta TYVIX}$. This row shows the well-known size effect in form of higher average returns for small-cap stocks. This pattern is also found among low- and (almost among) medium-, but not among high $\beta_{\Delta TYVIX}$ stocks. Whether there is a new, orthogonal size factor among post-crisis US bank stocks, as Gandhi and Lustig (2015) report, cannot be seen from table 6.3.

TABLE 6.3: **Double-Sort by Size and $\beta^i_{\Delta TYVIX}$**

This table shows the average monthly return, standard deviations (round brackets) and market betas (triangular brackets) of nine portfolios constructed by monthly rebalancing all bank stocks in the CRSP daily file depending on their current market capitalization and their past-month covariance with the first-difference of the TYVIX treasury volatility index. The bottom row shows a combination of the respective three portfolios above and the right column of the respective three portfolios to their left.

$\beta^i_{\Delta TYVIX}$	Market Equity			
	Big	Middle	Small	All
High	1.02 (6.78) <1.34>	1.18 (5.45) <1.02>	1.09 (4.84) <0.61>	1.1 (5.69) <0.99>
Medium	0.86 (6.54) <1.26>	0.85 (5.22) <0.92>	1.38 (4.38) <0.56>	1.03 (5.38) <0.91>
Low	0.64 (7.31) <1.5>	0.72 (5.84) <1.06>	1.2 (5.17) <0.70>	0.85 (6.11) <1.09>
All	0.84 (6.88) <1.37>	0.91 (5.5) <1.00>	1.22 (4.8) <0.62>	0.99 (5.73) <1.00>

Chapter 7

Conclusion

The question to be answered by this thesis was whether *uncertainty* is a priced risk-factor in the cross-section of expected stock returns and thus, should be included into linear factor models trying to explain the dispersion in asset's average returns.

To that end, the paper of Ang et al. (2006) was replicated. The results thus obtained are satisfactorily close to theirs, indicating a clean implementation on both their and my part. Therefore, the following results can be trusted.

Over the sample of 1986 to 2000, five portfolios with significant dispersion in their exposure to innovations in the VXO index (1:low to 5:high) show a significant and monotone decrease in average returns. The time-series pricing errors at the monthly frequency of the benchmark factor models CAPM, FF-3 and FF-5 show the same largely monotone, decreasing pattern. Both results are consistent with the hypothesis that investors are willing to accept lower expected returns on stocks that positively covary with innovations in uncertainty, as these stocks provide intertemporal hedges against such increases. The factor-mimicking portfolio used to obtain these results has low correlations with common risk factors. Controlling for momentum-effects influences results, but leaves the central conclusions intact. Thus, over this period, uncertainty-risk seems to have been priced in the cross-section of expected returns.

Over the sample of 1986 to 2018, the dispersion in average returns between the five portfolios mentioned above is still significant, but purely driven by the extreme portfolios 1 and 5. The pricing errors of benchmark factor models retain their largely monotone, decreasing pattern, but CAPM and FF-3 pricing errors are significant only for portfolio 5 while the pricing errors of FF-5 are not significant for any of the five portfolios. Thus, over the whole sample, there is some evidence in favor of an uncertainty-risk factor, but it is not sufficient.

Additionally, average returns of a zero-cost portfolio that goes long (short) stocks with high (low) exposure to uncertainty-risk have (from a negative start) generally decreased from 1990 to 2002 and generally increased since then. A significantly negative average return on such a spread portfolio should occur if uncertainty-risk is priced. The general increase in supportive evidence up to the factor's publication and subsequent general decrease in supportive evidence suggests the factor might not be systematic and instead be slowly arbitraged away. Also, if the remarkably linear pattern in spread portfolio average returns since 2009 continues, future studies of the VXO in the cross-section will probably not find those average returns to be significantly negative anymore. Therefore, I expect the non-sufficient evidence mentioned above to weaken further in the future.

Yet, the VXO is only one possible proxy for uncertainty. An investigation of the TYVIX implied treasury volatility index among post-crisis US bank stocks indicates a positive price of interest-rate uncertainty-risk among these stocks (i.e. higher covariance with the TYVIX seems to go along with higher average returns). The indications in this direction are not significant and serious objections to the suitability of the Ang et al. (2006)-procedure for such a small subset of stock, over a comparatively small period of time, arose. Nonetheless, the empirical support for a positive price of interest-rate uncertainty-risk among post-crisis US bank stocks is remarkable in so far as the effect is opposite to what was found for VXO among all stocks over 1986 to 2018.

In conclusion, I cannot reject the idea of an uncertainty-risk factor that partially explains the dispersion in assets' average returns, nor can I wholeheartedly embrace the concept. Instead, my thesis suggests there might be different aspects to uncertainty with regards to its pricing in the cross-section: Different subsets of stocks might require separate uncertainty-proxies as factors. Therefore, instead of giving a definite answer to the question whether uncertainty-risk is a significant factor in the cross-section of expected returns, this thesis shows a potentially fruitful direction for further research into uncertainty-risk.

Appendix A

Extensions of Chapter 6

TABLE A.1: **ΔTYVIX in the Cross-Section of Stock returns: 1986 - 2018**

For each month between January 1986 and December 2018 the daily returns of all NYSE, NASDAQ and AMEX stocks are regressed on MKT and $\Delta TYVIX$. The stocks are then divided into 5 portfolios from lowest $\beta^i_{\Delta TYVIX}$ (portfolio 1) to highest $\beta^i_{\Delta TYVIX}$ (portfolio 5). Thus, the 5 portfolios are rebalanced at the end of each month. Their monthly returns are given as the value-weighted average of their current constituents. Column II reports the average and column III the standard deviation of the 395 monthly total (not excess) returns for each portfolio, as well as a zero-cost portfolio that goes long portfolio 5 and short portfolio 1. Column IV gives their average market share. Columns V to VII contain the intercepts in monthly regressions of the portfolio returns on the market return, the FF-3 factors and the FF-5 factors, respectively. They can be interpreted as pricing errors of the respective model. Column 1 under the sub-heading *Factor Loadings* reports the time-series average of equal-weighted monthly averages of $\beta^i_{\Delta TYVIX}$ of consitituent stocks for each portfolio. The third-to-last column gives the same for $\beta^i_{\Delta FTYVIX}$, with FTYVIX being the daily factor constructed by monthly rebalancing the 5 portfolios so as to match daily innovations in the TYVIX as closely as possible. In contrast to the two preceding columns, the second-to-last column reports the time-series average of the monthly $\beta^i_{\Delta TYVIX}$ of the portfolios directly, while controlling for the market factor. The last column reports the $\beta^i_{\Delta FTYVIX}$ coefficients in the regression of monthly portfolio returns over the whole sample on a constant, the FF-3 factors and the FTYVIX factor. Square brackets contain robust Newey-West t-statistics. The *joint-test p-values* are based on an F-test by Gibbons, Ross, and Shanken (1989).

							Factor Loadings			
I Rank	II Mean	III Std. Dev.	IV % Mkt Share	V CAPM Alpha	VI FF-3 Alpha	VII FF-5 Alpha	Pre-Formation $\beta\Delta$ VIX	Pre-Form β FVIX	Next Month Post-Form $\beta\Delta$ VIX	Next Month Post-Form β FVIX
1	0.74	6.17	8.1%	-0.33	-0.29	-0.05	-3.39	-3.66	-0.014	-0.82
				[-2.45]	[-2.33]	[-0.43]				[-0.13]
2	0.91	4.54	25.6%	0.00	-0.01	-0.01	-0.81	-0.91	-0.002	-4.35
				[0.01]	[-0.15]	[-0.25]				[-1.39]
3	0.94	4.10	30.8%	0.09	0.07	0.17	-0.01	-0.02	0.005	-2.3
				[2.09]	[1.64]	[0.36]				[-1.12]
4	0.96	4.38	26.3%	0.07	0.06	0.00	0.77	0.86	0.015	1.46
				[1.29]	[1.13]	[0.08]				[0.51]
5	0.83	5.75	9.2%	-0.21	-0.16	-0.07	3.28	3.43	0.037	14.4
				[-1.97]	[-1.61]	[-0.66]				[2.37]
5-1	0.09			0.12	0.13	-0.02				
	[0.53]			[0.76]	[0.78]	[-0.08]				
Joint test p-value				0.10	0.07	0.95				0.00

TABLE A.2: **Factor Correlations: TYVIX 1986 - 2018**

On the left side, the mean and standard deviation of both the first-difference of the TYVIX and of the FTYVIX factor are given at the daily (top) and monthly (bottom) frequency. On the right side, their contemporaneous correlations with each other are given at the daily (panel A) and monthly (panel B) frequency . In addition, panel B contains correlations with common cross-sectional risk-factors. MKT, SMB and HML were proposed in Fama and French (1993). CMA and RMW were proposed in Fama and French (2015). UMD was constructed by Ken French. All 7 can be found on his website. LIQ was proposed in Pástor and Stambaugh (2003) and can be found on Robert Stambaugh's website.

			Panel A: Daily Correlations								
	Mean	Std dev	FTYVIX	Δ TYVIX							
Δ TYVIX	0.00	0.69	0.49	1.00							
FTYVIX	0.00	0.36	1.00	0.49							
			Panel B: Monthly Correlations								
			FTYVIX	Δ TYVIX	MKT	SMB	HML	UMD	LIQ	RMW	CMA
Δ TYVIX	-0.01	1.22	0.03	1.00	-0.1	0	0	-0.02	-0.09	0.08	0.06
FTYVIX	-0.06	1.79	1.00	0.03	-0.21	-0.06	0.05	-0.06	-0.04	0.02	0.13

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