Essays on Catastrophe Bonds Mutual Funds

A thesis of

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Note

This thesis is organized into four self-contained chapters, which is attained by allowing for some redundancies in the framework and methodology sections of the the first two chapters and appendices across chapters. The first two chapters are related in terms of some of the methodological framework.

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Abstract

This thesis focuses on the analysis of Catastrophe bond mutual funds [**CBMFs**] and is organized into four chapters.

The first chapter, *"An identification-robust analysis of Catastrophe bond mutual funds: zero-beta neutrality under tradability"*, offers identification-robust evidence on whether CBMFs are zero-beta based on the analysis with only tradable risk factors. Statistical significance of factor risk premiums and cross-sectional loadings is examined in a multivariate, identification-robust setting to inform on the zero-beta performance of CBMFs. The latter is assessed against the Capital Asset Pricing Model [**CAPM**] without the risk-less asset proposed by Black (1972) [**BCAPM**], Quadratic CAPM, Cummins-Weiss, Fama-French-Carhart benchmarks and models with Fontaine and Garcia (2012) and Pástor and Stambaugh (2003) liquidity factors. Multiple markets are considered individually and jointly. Beta pricing inference proceeds using the method of Beaulieu, Dufour and Khalaf (2013) robust to weak identification. Instead of non-tradable factors, their mimicking portfolio returns are used in the analysis to facilitate tradable-only factor setting. Results indicate that coskewness, funding liquidity and fixed-income factors are often priced or incur significant factor betas. There is also evidence of risk premiums and joint beta significance for stock, corporate bond and commercial mortgage-backed securities benchmarks. Empirical findings overall suggests that CBMFs underperformed as zero-beta assets.

The second chapter, *"Zero-beta inference on Catastrophe bond mutual funds: identification-robust evidence with non-tradable factors"*, examines formally the zero-beta neutrality of CBMFs allowing for some risk factors to be non-tradable. Zero-beta analysis focuses on cross-sectional betas with their joint significance tested for each factor. This is augmented with inference on risk prices and the zero-beta rate to assess whether factor risks are priced. CBMFs are modeled in the QCAPM setting with either stock, corporate bond, government bond or commercial mortgage-backed security [**CMBS**] market return and its square as respectively tradable and non-tradable factors. The zero-beta performance of CBMFs is also assessed against an extended BCAPM benchmark with either Fontaine and Garcia (2012) or Pástor and Stambaugh (2003) non-tradable liquidity factor considered in addition to the tradable market return. Inference on risk prices and the zero-beta rate builds on the method of Beaulieu, Dufour and Khalaf (2018) which remains exact and simultaneous for any sample size even if the parameter recovery is impaired. Empirically, although identification strength diminishes in the setting with non-tradable factors, relaxing tradability improves model fit across all benchmarks. In particular, QCAPM (re-

gardless of the market) is no longer rejected for any period and so is the model with the funding liquidity factor. Goodness-of-fit also improves for the model with the marketwide liquidity factor. In periods for which models were rejected under factor tradability, allowing for some factors to be non-tradable also yields set estimates for the zero-beta rate and risk prices that are informative for beta pricing. In particular, this reveals evidence of priced coskewness risk across all markets over the long-run and for stock, corporate bond and CMBS benchmarks after the 2007-09 US recession. In the same periods, funding liquidity risk is also priced and so is the marketwide liquidity risk over the full sample. Given significant betas on the market return, the latter prevails as a relevant factor even in a setting with other factors being non-tradable. Overall, there is evidence suggesting that CBMFs deviated from performing as zero-beta investments with coskewness and liquidity as contributing factors. These results reinforce findings in the Chapter 1.

The third chapter, *"An alpha and risk analysis of Catastrophe bond mutual funds: exact, simultaneous inference"*, examines CBMFs in terms of their ability to produce a positive alpha and the extent of their sensitivity to the developments in financial markets. Inference on alphas and the riskiness of CBMFs relies on exact, simultaneous confidence sets assembled respectively for cross-sectional intercepts and factor loadings in the multivariate linear regression [**MLR**] model. Set construction proceeds using the analytical inversion procedure of Beaulieu, Dufour and Khalaf (2018) in a Least-Squares case and its extension to a Student-t setting. Proposed in this chapter, the extension involves replacing the Fisher-based cut-off point in the analytical solution of Beaulieu, Dufour and Khalaf (2018) with its simulation-based counterpart obtained under Student-t errors. The empirical analysis of CBMFs reveals evidence of a positive alpha following the 2011 Tohoku earthquake in Japan and indicate that CBMFs are likely to have at most moderate sensitivity to fluctuations in financial markets. These results are robust against CAPM, QCAPM and Fama-French benchmarks and observed in both Gaussian and Student-t settings.

The fourth chapter, *"Endogeneity in a zero-beta analysis: joint, finite sample inference on Catastrophe bond mutual funds"*, revisits the zero-beta assessment of CBMFs taking into account factor endogeneity. In particular, this chapter extends the univariate Durbin-Wu-Hausman [**DWH**] test (Durbin, 1954; Wu, 1973; Hausman, 1978) of exogeneity to a multivariate setting. Unlike the univariate DWH test, the proposed multivariate extension allows to assess factor exogeneity jointly across equations. This chapter also proposes an extended version of the multivariate Wilks-based instrumental variables [**IV**] test of Dufour, Khalaf and Kichian (2013) to a setting with regressors, and consequently their instruments, that remain the same *across equations*. Both extended tests allow for possibly non-Gaussian errors and maintain size correctness for a sample with any number of observations even in the setting with weak instruments. Applying the extended methods to the analysis CBMFs provides evidence against joint factor exogeneity in some cases across CAPM and QCAPM in both Gaussian and Student-t settings. In some periods when the joint factor exogeneity is rejected, results for the zero-beta analysis differ depending on whether the IV-based or non-IV test was applied. Unlike in the case without instrumenting, extended Wilks-based IV test of joint beta significance is significant at the 5% level before the 2007-09 US recession for both CAPM and QCAPM regardless of the distributional setting (Gaussian or Student-t). The same result also obtains for QCAPM during the economic downturn. Over the long-run, there is evidence of jointly significant factor loadings obtained with and without instrumenting. Overall, empirical results suggest that performance of CBMFs differs from that of zero-beta assets.

Thesis Introduction

Launched at the start of the new millennium, Catastrophe bond mutual funds [**CBMFs**] represent an important new type of investment. For reinsurance markets, CBMFs are a vital supplier of alternative funding through their large, diversified holdings of Catastrophe bonds. For investors, CBMFs could be valuable as assets that aim to deliver "... a stable return that is higher than the risk-free interest rate, with a low correlation to fluctuations in financial markets" and are structured in a way that protects against most of the exposure to counterparty or credit risks (LGT Capital Partners 2015). It formally follows from these claims that CBMFs may produce a positive alpha as a spread over the risk-free benchmark and could perform with little exposure to systematic risk that is characteristic of zero-beta assets. Since the default of underlying Catastrophe bonds is conditional on the occurrence of natural disasters and in view of low correlations between catastrophic events and financial assets, CBMFs may well be zero-beta assets (Litzenberger, Beaglehole and Reynolds, 1996). Yet, the default of some Catastrophe bonds as a fallout of extreme impairment of their collateral and the collapse of their major counterparty during the 2007-08 financial crisis, provides support to the contrary. This thesis formally examines whether CBMFs can produce a positive alpha and studies the relation of these funds vis-a-vis financial markets.

The first chapter focuses on assessing whether CBMFs are zero-beta assets in the setting with only tradable factors. This involves testing joint significance of cross-sectional loadings on each factor to examine the overall sensitivity of CBMFs to fluctuations in factors themselves. Further evidence on the zero-beta performance of CBMFs comes from examining the responsiveness of these funds to changes in the level of factor risk, i.e., testing whether factor risks are priced. Focusing on both factor risk prices and betas is consistent with the theoretical work in the asset pricing literature which implies that the contribution of a given risk factor to the expected asset returns is a product of a factor beta, measuring the risk, and the factor risk price (see, e.g., Sharpe, 1964; Black, 1972; Kraus and Litzenberger, 1976; Campbell, Lo and MacKinlay, 1997). In the setting without a riskless asset, a zero-beta investment is given by the asset with its expected return equal to the zero-beta rate.[1] For a given asset, the latter equality results when factor betas and/or risk prices are zero across all risk factors implying that expected asset return incorporates no risk compensation over the zero-beta rate. Given the above, a reliable inference on the zero-beta performance necessitates assessing both factor betas

[1] The zero-beta rate is an expected return on a portfolio with the least exposure to an idiosyncratic risk among all portfolios not exposed to the systematic market risk.

and risk prices. While previous studies on CBMFs, Catastrophe bonds or their market index focused only on factor loadings or correlations (Cummins and Weiss, 2009; Gomez and Carcamo, 2014; Gürtler, Hibbeln and Winkelvos, 2014; Braun, 2015; Carayannopoulos and Perez, 2015), we fill the gap in the literature by considering the sensitivity of CBMFs to fluctuations in both factors themselves and in factor risks (as measured by factor loadings).

Inference on whether factor risks are priced is based on the exact confidence set for the zero-beta rate constructed using the analytical procedure of Beaulieu, Dufour and Khalaf (2013). The latter method produces size-correct set estimate irrespective of the parameter identification strength and how large is the sample. The robustness to weak parameter identification is relevant given that the zero-beta rate is defined through a non-linear null hypothesis which may impair parameter recovery. Further, the significance of factor loadings is assessed jointly via the exact, multivariate Hotelling test (Hotelling, 1947). In terms of a joint assessment over the cross-sectional factor betas, the analysis in this chapter is novel relative to previous studies that focused on a single beta (or a correlation) for each risk factor (see, e.g., Cummins and Weiss, 2009; Gürtler et al., 2014; Carayannopoulos and Perez, 2015) and informs on the overall risk exposure of CBMFs.

The analysis proceeds in the setting with only tradable factors as is common in the asset pricing literature in the time-series setting (see Cochrane, 2001). This is achieved through the substitution of non-tradable factors with returns on their mimicking portfolios following the well-known practice theoretically motivated by Breeden (1979) and Huberman, Kandel and Stambaugh (1987). Mimicking returns result from adding together weighted base asset returns with weights depending on projection-based coefficients (see, e.g., Breeden, Gibbons and Litzenberger, 1989; Adrian, Etula and Tyler, 2014)

The zero-beta performance of CBMFs is assessed against multiple benchmarks including Fama-French-Carhart, Cummins-Weiss, models with liquidity factors as well as Capital Asset Pricing Model [**CAPM**] and Quadratic CAPM [**QCAPM**] based on either stock, corporate bond, government bond or commercial mortgage-backed security [**CMBS**] market factor. In terms of empirical results, there is evidence of priced risk or jointly significant betas for coskewness, funding liquidity and fixed-income factors across periods. These findings are new to the literature on CBMFs. Also, stock, corporate bond and CMBS factors are often priced and have nontrivial factor loadings. The analysis overall indicates that CBMFs fell short of performing as zero-beta assets.

Having examined the zero-beta neutrality of CBMFs in the setting with only tradable factors, the analysis of whether CBMFs are zero-beta in the second chapter relaxes the tradability restriction for some risk factors. This involves introducing non-tradable factors directly into the model instead of using their mimicking portfolio returns. Kleibergen and Zhan (2018) provide evidence that using mimicking returns as a substitute for non-tradable factors may lead to spurious inference on risk prices when these factors have little comovement with asset returns. In particular, mimicking returns could be constructed with pricing errors that distort pricing information conveyed in non-tradable factors. Further, noise introduced via the construction of mimicking returns could also invalidate inference on the joint significance of factor loadings. Given the above, the second chapter examines the zero-beta neutrality of CBMFs against QCAPM benchmarks with a squared market return incorporated directly as a non-tradable factor. In addition, models with a non-tradable liquidity factor of either Fontaine and Garcia (2012) or Pástor and Stambaugh (2003) are also considered.

In terms of focusing on both risk pricing evidence and joint significance of factor betas, the first two chapters are similar. Unlike chapter 1 which relies on set estimates for the zero-beta rate to inform on the beta pricing for all factors, this essay tests if non-tradable factors are priced based on the confidence sets estimated for their respective risk prices while inference on a single tradable factor is based on the zero-beta rate (see, e.g., Shanken, 1992; Beaulieu, Dufour and Khalaf, 2015, 2018). Confidence sets for the zero-beta rate and the risk prices are obtained using the analytical inversion-based procedure of Beaulieu, Dufour and Khalaf (2018). The latter method ensures exactness and simultaneity of resulting set estimates regardless of the parameter identification status. Using the approach invariant to the weak identification is of importance given that both risk prices and the zero-beta rate are introduced via the non-linear hypothesis that may undermine identification.

Compared to the analysis in the first chapter, relaxing the factor tradability improves the goodness-of-fit across all benchmarks, albeit parameter recovery becomes harder. In particular, QCAPM for any market and the model with the funding liquidity factor are no longer rejected in any period. Given the improved model fit, identification-robust set estimates for the zero-beta rate and the risk prices could be used to inform on whether factors are priced in the periods for which it was not possible in the first chapter due to model rejection. In particular, QCAPM results for all markets indicate that coskewness risk is priced over the full sample. Coskewness with respect to stock, corporate bond and CMBS markets is also priced after the 2007-09 US recession. Both marketwide and funding liquidity risks incur premiums after the recession. For the funding risk, this is also the case over the long-run. Given significant betas on the market return, the latter factor remains relevant even in the presence of non-tradable factors. Results in this essay are broadly consistent with those in the fist chapter and provide evidence against CBMFs performing as zero-beta assets.

The third chapter examines whether CBMFs deliver a positive alpha and how risk sensitive these funds are vis-a-vis financial markets. Inference on fund alphas proceeds based on cross-sectional intercepts in the multivariate linear regression [**MLR**] model. To assess the riskiness of CBMFs, the empirical strategy involves the MLR cross-sectional loadings on each factor. To evaluate either betas for a given risk factor or intercepts, the analysis relies on exact, simultaneous confidence sets obtained analytically for a cross-section of respective parameters via the inversion-based solution of Beaulieu, Dufour and Khalaf (2018) in the Least-Squares setting. For a given regressor, the method produces cross-sectional set estimates with a joint probability coverage. The statistical precision of the latter is maintained at the $(1-\alpha)$ confidence level with α indicating a significance level. As an extension of the above method to a Student-t case, this chapter proposes to adjust the inversion procedure by using the simulated cut-off point instead of the Fisher-based critical value. This involves simulating the null distribution for the underlying Hotelling statistic. In the extended Student-t case, the exactness and simultaneity of the resulting confidence sets is retained. The extended method is applied to assess CBMFs in the setting with Student-t errors.

Relative to previous studies on CBMFs, Catastrophe bonds or their market index, the alpha and risk analysis in the chapter 2 is similar in terms of the focus on respectively intercepts and factor loadings (see, e.g., Jensen, 1968; Connor and Korajczyk, 1986; Grauer, 2008; Kan and Wang, 2017; Fama and French, 1993; Cummins and Weiss, 2009; Gürtler, Hibbeln and Winkelvos, 2014; Gomez and Carcamo, 2014). Rather than considering a single parameter per regressor, this chapter differs by examining a cross-section of parameters on a given regressor (either a vector of constants or a risk factor) via exact, simultaneous confidence sets with a joint probability coverage. The latter allows to examine the alphas and riskiness jointly across mutual funds. The exact, simultaneous confidence sets aggregate information from multiple tests and contain only those parameter values for which these tests are not significant. This makes set estimates more informative as compared to the exact, joint test of Gibbons, Ross and Shanken (1989) [**GRS**] for intercepts or its counterpart for factor loadings as the GRS test only evaluates significance relative to zero.

According to empirical findings, there is evidence of a positive alpha for CBMFs after the 2011 Tohoku earthquake in Japan as most set estimates obtained for intercepts are strictly positive. This occurs in the CAPM, QCAPM and Fama-French settings regardless of whether errors are Gaussian or Student-t. Results across models and periods also indicate that although CBMFs may not be zero-beta given the presence of positive values in the confidence sets for factor betas, the exposure to factor risks is at most moderate as the upper set bounds, albeit positive, are fairly small.

The fourth chapter examines whether CBMFs are zero-beta assets in the setting that takes the factor endogeneity into account. Specifically, extending the univariate Durbin-Wu-Hausman [**DWH**] test of exogeneity (Durbin, 1954; Wu, 1973; Hausman, 1978), the chapter 4 proposes its multivariate version that allows to evaluate jointly across equations whether factors are exogenous. In addition, this chapter extends the multivariate, Wilks-based instrumental variables [**IV**] test of Dufour, Khalaf and Kichian (2013) to a setting where equations are identical in terms of regressors and instruments. Valid in the setting with possibly non-Gaussian errors, both extended tests are precise in terms of size irrespective of the sample length and remain reliable even if instruments correlate modestly with regressors that are being instrumented. The analysis of CBMFs proceeds using both extended tests proposed in the fourth chapter. Regardless of whether errors are Gaussian or Student-t, the joint factor exogeneity is rejected at 5% significance level for both CAPM and QCAPM benchmarks before the 2007-09 US recession. The DWH test is also significant at 10% level for the QCAPM benchmark during the economic downturn and over the full sample. Extended Wilks-based IV test of joint beta significance yields results that differ from those obtained without instrumenting in some cases when factor exogeneity does not hold. While the Wilks-based IV test of factor loadings being jointly zero is rejected for both CAPM and QCAPM before the recession, this is not the case for the non-instrumented joint test. The same finding obtains for the QCAPM during the period of economic turmoil. Over the full sample, factor betas are jointly significant based on both instrumented joint test and its counterpart without instrumenting. Overall, the IV-based results suggest that CBMFs underperform as zero-beta assets.

Overall, while evidence from Chapters 1, 2 and 4 indicate that CBMFs may not be strictly zero-beta assets, confidence sets reported for factor loadings in Chapter 3 cluster fairly tightly around zero suggesting a modest exposure to systematic market risks and a considerable diversification potential on the part of CBMFs.

Chapter One

An identification-robust analysis of Catastrophe bond mutual funds: zero-beta neutrality under tradability

1.1 Introduction

Catastrophe bond mutual funds [**CBMFs**] are often described as assets "...with low correlation to fluctuations in financial markets..." and a structure that eliminates most of the potential counterparty or credit risks (LGT Capital Partners, 2015). As such, CBMFs are often perceived as zero-beta neutral with respect to financial markets. These funds mostly comprise of Catastrophe bonds.[1] By design, the latter make coupon and principal payments and structured not to default unless a triggering natural disaster, like an earthquake or a tornado, occurs. With the default of the underlying bonds linked only to the catastrophe risk, CBMFs may indeed be zero-beta neutral. However, during the 2007-08 financial crisis, vulnerabilities in the structure of Catastrophe bonds emerged leading some of them to default due to exposure to systematic market risk. In particular, several Catastrophe bonds saw the value of their underlying collateral assets plummet rapidly and endured bankruptcy of their total return swap counterparty, Lehman Brothers. The compounded negative impact of the two channels resulted in the default of these bonds. The market for CBMFs was also affected indirectly, and investor perception of these funds as zero-beta neutral was shaken. This paper examines formally whether CBMFs are zero-beta neutral vis-a-vis financial markets.

Investigating whether CBMFs are zero-beta neutral is important for several reasons. First, if a perception of CBMFs as zero-beta neutral is unfounded, this could undermine the stability of the financial system. In particular, if CMBFs depart the zero-beta neutrality during periods of financial stress, it could amplify negative shocks and exacerbate volatility in financial markets. Given that the market for Catastrophe bonds has reached US $30 billion in 2017 and the role of CBMFs as their primary investor with nearly 60% share in new issues, there could be a pronounced impact on the financial system (Artemis, 2017; Aon Benfield, 2017b). Second, negative social outcomes could result if investors lose their savings that were misplaced due to an unreliable information about the zero-beta performance of CBMFs. Third, through their active investment in Catastrophe bonds, CBMFs are vital for reinsurance markets. In particular, nearly 30% of alternative capital for global property catastrophe reinsurance in 2017 was raised through Catastrophe

[1] Appendix A describes Catastrophe bonds in more detail.

bonds (Aon Benfield, 2017a). Hence, instability of CBMFs could also destabilize reinsurance markets. Providing formal evidence on the zero-beta performance of CBMFs could enhance functioning of financial and reinsurance markets and help investors to allocate their savings more efficiently.

Notwithstanding the relevance of examining whether CBMFs are zero-beta, little formal research has been devoted to the analysis of this issue. Relying on the pooled regression in the panel data setting, Cummins and Weiss (2009) find evidence that CBMFs comoved positively with financial benchmarks before mid-2008. While the estimated factor loadings are statistically significant, the relationship appears to be economically weak given small beta estimates suggesting that CBMFs may not have diverged that much from performing as zero-beta assets before mid-2008. Most existing studies examined the dynamics with financial benchmarks at the level of Catastrophe bonds or indices (see, for instance, Cummins and Weiss, 2009; Gomez and Carcamo, 2014; Gürtler, Hibbeln and Winkelvos, 2014; Braun, 2015; Carayannopoulos and Perez, 2015). Lacking inference on the risk prices, the analysis in these papers builds on point estimates for factor loadings or correlations. These studies overall suggest that Catastrophe bonds do not always achieve a zero-beta performance.

In terms of literary contributions, the novelty of this paper is threefold. First, this study examines both factor risk exposure and pricing to inform on the zero-beta neutrality of CBMFs. In particular, our zero-beta analysis tests joint significance of factor loadings to assess the overall exposure to systematic risk. This relies on the exact, multivariate Hoteling test statistic (Hotelling, 1947). The latter is a more general counterpart of the univariate Student-t measure. Previous literature on Catastrophe bonds and CBMFs has largely focused on beta significance or correlations with respect to financial market benchmarks (Cummins and Weiss, 2009; Braun, 2015; Carayannopoulos and Perez, 2015). While informative, assessing only significance of betas is insufficient as it ignores relevant information on beta pricing and could lead to a spurious inference on the zero-beta performance. As implied by the asset pricing relation in the setting without a riskless asset (see e.g., Black, 1972; Campbell, Lo and MacKinlay, 1997, Chapter 6.2.2), expected asset returns amount to a sum of the zero-beta rate and a compensation on each factor for the exposure to systematic risk.[2] The latter is a two-part component multiplying β, the extent of risk, by λ, the risk price. It is straightforward to see that the compensation term drops out if β and/or λ is zero. In this case, the asset is said to be zero-beta neutral and has expected return equal to the zero-beta rate. In this setting, an in-depth zero-beta

[2]Black (1972) considers the case when there is no risk-less asset. Instead of the latter, the model he proposes relies on a zero-beta portfolio with its expected return named as the zero-beta rate. This portfolio varies the least among all portfolios with no exposure to any systematic risk (for a discussion of the zero-beta rate and asset pricing tests based on the model of Black (1972) see Campbell, Lo and MacKinlay, 1997, Chapters 5 and 6).

analysis involves testing whether there is a risk premium on a given factor (**beta pricing** hereafter) in addition to checking its beta significance. This paper does both and in this regard fills the void in the literature on Catastrophe bonds and CBMFs.

Second, the analysis addresses an identification problem to precisely conduct the beta pricing inference. In particular, testing significance of the risk premium relies on the confidence set constructed for the zero-beta rate. The latter is defined by the model through a non-linear restriction on its intercept, which can lead to an identification problem. More precisely, when the sum of betas across factors is jointly (across equations) close to one, this undermines identification of the zero-beta rate. In the severe case when factor betas sum to one precisely, parameter identification fails completely and beta pricing inference cannot proceed. However, conventional inference methods fail to detect and reveal weak identification when it is present. The former provide no control over the probability of parameter coverage when identification fails and could be highly misleading for inference. These issues may explain the lack of a comprehensive zero-beta analysis on Catastrophe bonds and CBMFs that would incorporate information on beta pricing. This study fills the gap in the literature by facilitating robust inference on the risk premium using the method of Beaulieu, Dufour and Khalaf (2013). The latter approach produces an identification-robust confidence set for the zero-beta rate by inverting a pivotal Hotelling test defined for the restriction on the intercept. To invert the test, all admissible values of the zero-beta rate are considered one at a time, with the significance of the test assessed under each value. The resulting confidence set obtains as a collection of values for which the test is insignificant at level α. The set estimate produced via this method remains robust and exact regardless of the identification strength and sample size in the sense that parameter coverage is always controlled with the probability of $(1 - \alpha)$. If weak identification is detected, the robust method signals its presence through a confidence set that takes the form of a real line or a union of two disjoint sets. This helps avoid spurious inference and, depending on the severity of an identification problem, could be informative for beta pricing.

Third, the zero-beta inference on CBMFs in this study proceeds with an expanded set of benchmarks and extends beyond 2008. The analysis relies on the single-factor Capital Asset Pricing Model [**CAPM**] without the risk-less asset of Black (1972) [**BCAPM**] and its extension the Quadratic CAPM [**QCAPM**].[3] As argued by Barone-Adesi (1985) and Barone-Adesi, Gagliardini and Urga (2004), the latter model allows to account for the market coskewness risk via the mimicking portfolio on the squared market return considered as a second factor. It has been theorized in the literature that investors may seek to hold portfolios with a positive market coskewness. In particular, Kraus and

[3]The BCAPM of Black (1972) extends the CAPM initially developed by Sharpe (1964), Lintner (1965*a*,*b*).

Litzenberger (1976) develop the Three-Moment CAPM in which expected asset returns depend on the coskewness beta in addition to the traditional market beta. Further, given their extreme-event nature, CBMFs may display non-linearity in their relation with financial markets. Incorporating a portfolio that mimics the squared market return could account for the non-linear dynamics and improve model fit. Coskewness risk and non-linearity have not been considered to date to inform on the zero-beta neutrality of CBMFs, to the best of our knowledge. This study broadens the literature in this regard.

In addition, the analysis covers Fama-French factors that were found to be relevant for modeling stock and bond returns (Fama and French, 1993). These include High-minus-Low [**HML**] and Small-minus-Big [**SMB**] stock portfolios designed to mimic factors capturing other sources of systematic risk linked to firm size and book-to-market equity value. To inform on whether zero-beta performance of CBMFs is invariant to interest rate and default risks, the analysis also incorporates TERM and DEF fixed-income factors. The momentum factor of Carhart (1997) is also considered jointly with Fama-French factors to account for the asset price persistence. To the best of our knowledge, the role of these factors for the zero-beta neutrality of CBMFs has not been previously explored. This paper expands the analysis available in the literature along this dimension.

The relevance of the liquidity risk for various assets has been well documented (see, e.g., Hu, Pan and Wang, 2013; Fontaine, Garcia and Gungor, 2016). To assess whether zero-beta neutrality of CBMFs holds regardless of the funding conditions that prevail in financial markets, this paper considers the funding liquidity factor of Fontaine and Garcia (2012) together with either BCAPM or Fama-French model. More precisely, a mimicking portfolio for the first difference of this factor is considered. Similar estimation is carried out with the market liquidity factor of Pástor and Stambaugh (2003). As far as we know, a zero-beta analysis that would account for the liquidity risk is unavailable in the literature on CBMFs to date. Our analysis addresses this gap.

In addition, this paper extends the zero-beta analysis of CMBFs vis-a-vis different financial markets beyond 2008 and to the identification-robust setting. In particular, the model of Cummins and Weiss (2009, p.535) with stock return, corporate bond return and the log of corporate bond yield is considered. Further, BCAPM is estimated individually for stock, corporate bond, government bond and commercial mortgage-backed securities [**CMBS**] market benchmarks. Finally, results for a combined model with all the benchmarks are also provided.

Empirical analysis provides results over the entire study period between 11/2004 - 12/2015. In addition, it is of particular relevance to assess the zero-beta neutrality of CBMFs in the context of the 2007-08 financial crisis and the ensuing recession. There are channels through which the performance of CBMFs may have been affected during the crisis and thereafter. Prior to the crisis, it was common to store proceeds from selling

Catastrophe bonds as a collateral consisting of highly rated, complex financial products including CMBS. As the US housing market collapsed and financial markets became unstable, many of these products diminished in value. This, in turn, undermined Catastrophe bonds and CBMFs that invested in them. In addition, the Lehman Brothers served as a Total Return Swap Counterparty for several Catastrophe bonds. The company's collapse compounded the pre-existing vulnerability with the collateral assets leading some of these Catastrophe bonds to default. In this case, the unwinding of Catastrophe bonds did not occur due to a natural disaster, but was triggered by severe exposure to the systematic risk. To examine how the zero-beta performance of CBMFs evolved over time, this paper also provides results for sub-periods before, during and after the 2007-09 US recession.[4]

Empirically, there is evidence that the zero-beta neutrality of CBMFs does not hold. This is broadly congruent across models and markets. In particular, many factors incur risk premiums and/or significant betas in sub-periods. Full-sample analysis provides similar findings. Factors with a pronounced impact include coskewness, funding liquidity and those capturing interest rate and default risks, i.e. TERM and DEF respectively. Specifically, QCAPM results indicate that coskewness is often priced or has non-trivial betas across markets. The augmented BCAPM and Fama-French model reveal the funding risk premium over the full sample, before and after the recession. Results from the Fama-French versions also suggest that TERM and DEF are both priced in some cases. The latter also at times displays betas jointly different from zero. These are novel results to the literature on CBMFs.

Moreover, there is indication of pricing and risk exposure with respect to the stock market benchmark. This occurs across multiple models. The corporate bond market also appears relevant as evidenced by results from BCAPM, QCAPM and the Cummins-Weiss model. CMBS emerges as another relevant market in addition to stocks and corporate bonds. In particular, when considered in a joint setting with other benchmarks, the CBMS beta risk is either priced, jointly significant or both. The overall indication is that CBMFs fell short of achieving zero-beta neutrality.

The outline for what follows is summarized below. Section 1.2 introduces notation and describes the general framework for testing the zero-beta neutrality. Section 1.3 presents tests and the inversion procedure. The data description is available in Section 1.4. A summary of empirical results follows in Section 1.5 with conclusions offered in Section 1.6.

[4]The overall sample is divided into three sub-periods in line with the US recession dates of the National Bureau of Economic Research.

1.2 Notation and Framework

Consider a multifactor zero-beta model without a riskless asset [**ZBM**], which was initially proposed by Black (1972) as a single-factor model [**BCAPM**] and later extended to a more general setting with multiple factors (see, e.g., Campbell, Lo and MacKinlay, 1997, Chapter 6.2.2). In particular, let $(T \times 1)$ vector r_i, $i = 1, \ldots, n$, and $(T \times q)$ matrix $\mathcal{F} = [\mathcal{R}_1, ..., \mathcal{R}_q]$ denote real returns on, respectively, portfolio of assets i and q tradable factors, with $k = q + 1$. In the unconstrained case, the model takes the following form:

$$r_i = \iota_T a_i + \mathcal{F} b_i + u_i, \qquad i = 1, \ldots, n, \tag{1.1}$$

where b_i is a $(q \times 1)$ vector of factor sensitivities and u_i is a $(T \times 1)$ vector of random disturbances. Throughout, ι_z indicates a $(z \times 1)$ vector of ones. A tradable factor corresponds to a portfolio of traded securities.

In this setting, beta sensitivity tests the joint statistical significance of factor loadings via the multivariate Hotelling statistic. Specifically, we examine the following joint null hypothesis defined for a cross-section of beta loadings on each factor:

$$H_0^{(1)} : b_{ij} = 0, \quad i = 1, \ldots, n, \quad j \in \{1, \ldots, q\}. \tag{1.2}$$

The beta pricing analysis proceeds in the context of the constrained model. In the restricted case, real returns are specified in deviation from the zero-beta rate γ_0, that is, the expected return on a zero-beta portfolio. A defining characteristic of the latter is the absence of comovement with the risk factors $\mathcal{F}$. While there can be several portfolios that satisfy the no-comovement requirement, the zero-beta portfolio is the least volatile from among those (Campbell, Lo and MacKinlay, 1997, Chapter 6.2.2). Formally, the constrained model takes the form:

$$r_i - \iota_T \gamma_0 = (\mathcal{F} - \iota_T \gamma_0 \iota_q') b_i + u_i, \quad i = 1, \ldots, n. \tag{1.3}$$

The above model can be restated as follows:

$$r_i = \iota_T \gamma_0 (1 - \iota_q' b_i) + \mathcal{F} b_i + u_i, \quad i = 1, \ldots, n, \tag{1.4}$$

with the following non-linear restriction imposed on the intercept:

$$H_0^{(2)}(\gamma_0) : a_i = \gamma_0 (1 - \iota_q' b_i), \quad i = 1, \ldots, n. \tag{1.5}$$

Beta pricing analysis relies on the confidence set estimated for γ_0. The inference proceeds in the cross-sectional setting (see, e.g., Shanken and Zhou, 2007). More precisely, averaging (1.3) across time gives the following:

$$\begin{aligned} \bar{r}_i &= \gamma_0 (1 - \iota_q' b_i) + \bar{\mathcal{F}} b_i + \bar{u}_i \quad i = 1, \ldots, n \\ &= \gamma_0 + (\bar{\mathcal{F}} - \gamma_0 \iota_q') b_i + \bar{u}_i \quad i = 1, \ldots, n, \end{aligned} \tag{1.6}$$

where $\bar{r}_i$ and $\bar{\mathcal{F}} = (\bar{\mathcal{R}}_1, ..., \bar{\mathcal{R}}_q)'$ collect mean returns on portfolio i and q tradable factors respectively. Equation (1.6) implies that a factor j is not priced if the following relation holds true:

$$\bar{\mathcal{R}}_j - \gamma_0 = 0, \quad j = 1, \ \ldots \ , \ q. \tag{1.7}$$

It further follows from (1.7) that a factor j is priced if the confidence set for γ_0 does not cover j's mean factor return, $\bar{\mathcal{R}}_j$.

This setting facilitates zero-beta inference on CBMFs. The analysis covers different ZBM specifications. Table 1.2 provides a list of all estimated models. It is informative to assess the zero-beta performance of CBMF's against a traditional single-factor BCAPM proposed by Black (1972). In this case, ZBM reduces to one benchmark. Since zero-beta analysis concerns with the relation of CBMFs vis-a-vis financial markets as a whole, it is of importance to estimate the BCAPM separately for stock, corporate bond, government bond and CMBS benchmarks. Estimating a joint model covering all four benchmarks allows to assess relative risk exposure and pricing.

The analysis further extends to the QCAPM which accounts for the coskewness risk. Theoretical groundwork introducing coskewness as a relevant factor can be traced to Kraus and Litzenberger (1976).[5] Aside from the traditional market beta, their Three-Moment CAPM relates expected asset returns to the coskewness beta. This aims to incorporate investor preference for positive portfolio coskewness with the market. Barone-Adesi (1985), and more recently Barone-Adesi, Gagliardini and Urga (2004), argue that beta on the mimicking portfolio for the squared market return captures the coskewness risk. Zero-beta inference on CBMFs proceeds by estimating QCAPM with a mimicking portfolio for the squared market return. Estimation involves four different QCAPM models specified for either stock, corporate bond, government bond or CMBS market return and its square. Appendix D describes the procedure for constructing mimicking portfolios.

Cummins and Weiss (2009) study zero-beta performance of CBMFs prior to June 2008 in a three-factor model with stock index return, BBB corporate bond index return and Baa corporate bond yield. Their analysis proceeds in a panel data setting and suggests that CBMFs were close to being zero-beta before mid-2008. In this paper, the three-factor model of Cummins and Weiss (2009) is estimated for CBMFs beyond 2008 using methods that allow for exact, identification-robust, joint inference on their zero-beta performance. This estimation is complementary to the analysis in Cummins and Weiss (2009).

Asset pricing literature documents other factors capturing additional sources of systematic risk besides the traditional market beta. In particular, Fama and French (1993) report that High-minus-Low (HML) and Small-minus-Big (SMB) portfolios are relevant for explaining fluctuations in stock and bond returns. These portfolios relate to risks with

[5] Models incorporating cokurtosis in addition to covariation and coskewness have also been proposed in the literature (see, e.g., Fang and Lai, 1997; Back, 2014). It may be of interest to also examine the role of cokurtosis risk in assessing CBMFs. However, as has been shown in previous studies, skewness and kurtosis are highly interrelated. This can introduce multicollinearity problem and weaken identification undermining inference on factor betas and risk prices (Wilkins, 1944; Schopflocher and Sullivan, 2005).

links to firm size and book-to market equity value. Also, fixed-income factors TERM and DEF, related to interest rate and default risks, were found to have a strong explanatory power for corporate and government bond returns (Fama and French, 1993). Estimating five-factor Fama-French model with HML, SMB, TERM, DEF and excess market return allows to assess relevance of these factors for the zero-beta performance of CBMFs.

Carhart (1997) proposes a momentum factor that accounts for the asset price persistence. Literature provides evidence of a momentum profit for stocks (Jegadeesh and Titman, 1993, 2001). Estimating a model with Fama-French and momentum factors considered jointly informs on whether persistence is important and reveal which factors are more relevant for the zero-beta inference on CBMFs.

CBMFs may fall short of achieving the zero-beta neutrality due to the market-wide liquidity risk. Estimating a two-factor model with the BCAPM market return and the traded liquidity factor [**LIQT**] of Pástor and Stambaugh (2003) could inform in this regard. To gain further insights, a combined model with Fama-French and LIQT factors is also considered.

Fontaine, Garcia and Gungor (2016) report strong evidence of priced funding risk for a range of asset returns. To assess whether performance of CBMFs is zero-beta neutral regardless of funding constraints, it is of interest to consider a model that incorporates the funding liquidity factor of Fontaine and Garcia (2012) together with either BCAPM or Fama-French benchmark. In particular, estimation proceeds using a mimicking portfolio for the first difference of this factor, [**MΔFL**].

Model (1.1) can be restated in a more general form:

$$Y = XB + U \tag{1.8}$$

where $Y = \left[\begin{array}{ccc} Y_1 & ... & Y_n \end{array}\right]$ corresponds to a $(T \times n)$ matrix of regressands, X is a $(T \times k)$ full-column matrix with time-series on q explanatory variables and a vector of ones. Regression coefficients are assembled into $(k \times n)$ matrix B (intercepts in the 1st column) with the associated OLS estimator denoted by $\hat{B}$, while $U = \left[\begin{array}{ccc} U_1 & ... & U_n \end{array}\right]$ is a $(T \times n)$ matrix of stochastic disturbances with the corresponding OLS-based residuals given by $\hat{U}$. Specifically, model (1.1) arises as a special case of (1.8) when the variables are set as follows:

$$\begin{aligned}
&Y = \left[\begin{array}{ccc} r_1, & ... & , r_n \end{array}\right], \quad r_i = \left(\begin{array}{ccc} r_{1i}, & ... & , r_{Ti} \end{array}\right)', \quad i = 1, \dots, n \qquad (1.9)\\
&X = \left[\begin{array}{cc} \iota_T, & \mathcal{F} \end{array}\right], \quad \mathcal{F}\ is\ (T \times q), \quad B = \left[\begin{array}{cc} a, & b' \end{array}\right]', \quad a = \left(\begin{array}{ccc} a_1, & ... & , a_n \end{array}\right)'\\
&b = \left[\begin{array}{ccc} b_1', & ... & , b_q' \end{array}\right]'\ is\ (q \times n), \quad b_j = \left(\begin{array}{ccc} b_{j1}, & ... & , b_{jn} \end{array}\right)', \quad j = 1, \dots, q, \quad k = q + 1,
\end{aligned}$$

with the corresponding OLS-based estimators:

$$\hat{B} = \left[\begin{array}{cc} \hat{a}, & \hat{b}' \end{array}\right]' = (X'X)^{-1}X'Y, \quad \hat{U} = Y - X\hat{B}, \quad \hat{S} = \hat{U}'\hat{U}, \quad \hat{\Sigma} = \frac{\hat{S}}{T}. \tag{1.10}$$

For the exposition that follows, it is convenient to rewrite the null hypotheses stated above more generally using matrix notation. Indicating by $\mathcal{O}_{1\times n}$ a $(1\times n)$ vector of zeros, the Hotelling null hypothesis in (1.2) takes the form:

$$H_0^{(1)}: e_k[j]'B = \mathcal{O}_{1\times n}, \quad j \in \{2,\ \dots\ ,\ k\}, \tag{1.11}$$

where k-dimensional selection vector $e_k[s]$ has a single non-zero element in row s equal 1.

Further, ZBM restriction on the intercept in (1.5) is also restated as follows:

$$H_0^{(2)}(\gamma_0): (1,\gamma_0)D = \mathcal{O}_{1\times n}, \quad D = \left[\ a,\ (\iota_q' b - \iota_n')'\ \right]', \quad \textit{for some unknown}\ \gamma_0, \tag{1.12}$$

with the associated OLS-based estimator for D:

$$\hat{D} = \left[\ \hat{a},\ (\iota_q'\hat{b} - \iota_n')'\ \right]'. \tag{1.13}$$

In the multifactor setting, beta pricing methodology relies on a transformation of the model (1.8) obtained via matrix pre-multiplication as in Beaulieu, Gagnon and Khalaf (2015). Specifically, partition matrix with explanatory variables as follows:

$$X = [\iota_T, \mathcal{R}_1, \mathcal{F}_a], \quad \mathcal{F}_a = [\mathcal{R}_2, ..., \mathcal{R}_q], \tag{1.14}$$

and let additional variables to be given by:

$$\begin{aligned} & Y_1 = Y - \mathcal{R}_1\iota_n', \quad \mathcal{F}_1 = \mathcal{F}_a - \mathcal{R}_1\iota_{q-1}' \\ & M_1 = I_T - \mathcal{F}_1(\mathcal{F}_1'\mathcal{F}_1)^{-1}\mathcal{F}_1', \\ & \tilde{Y} = M_1 Y_1 = M_1(Y - \mathcal{R}_1\iota_n'), \\ & \tilde{\mathcal{F}} = M_1\mathcal{R}_1, \quad \tilde{X} = \left[\ M_1\iota_T,\ \tilde{\mathcal{F}}\ \right], \end{aligned} \tag{1.15}$$

where $\tilde{\mathcal{F}}$ is $T\times\tilde{q}$ and $\tilde{X}$ is $T\times\tilde{k}$ matrices.

Given this notation, the transformed model takes the form:

$$M_1 Y = \tilde{X}\tilde{B} + \tilde{U} \quad \Leftrightarrow \quad \tilde{Y} = \tilde{X}D + \tilde{U}, \tag{1.16}$$

where

$$\tilde{B} = \left[\ a,\ (\iota_q' b)'\ \right]' \quad D = \left[a,\ (\iota_q' b - \iota_n')'\right]',$$

estimating (1.16) by OLS yields:

$$\hat{\tilde{B}} = (\tilde{X}'\tilde{X})^{-1}\tilde{X}'(M_1 Y), \quad \hat{D} = \left[\hat{a},\ (\iota_q'\hat{b} - \iota_n')'\right]', \tag{1.17}$$

$$\hat{\tilde{S}} = \hat{\tilde{U}}'\hat{\tilde{U}}, \quad \hat{\Sigma} = \frac{\hat{\tilde{S}}}{T}, \quad \hat{\tilde{U}} = M_1 Y - \tilde{X}\hat{\tilde{B}}.$$

More generally, beta pricing methodology described in the following section depends on whether a single-factor or multifactor model is considered. Formally, we have:

$$\dot{Y} = \dot{X}\dot{B} + \dot{U}, \tag{1.18}$$

$$H_0^{(2)}(\gamma_0): (1,\gamma_0)D = \mathcal{O}_{1\times n}, \quad D = \left[a,\ (\iota_q' b - \iota_n')'\right]', \quad \textit{for some unknown}\ \gamma_0, \tag{1.19}$$

where $\dot{X}$ is $(T\times\dot{k})$ and

$$\begin{aligned} &\dot{Y} = Y,\ \dot{X} = X,\ \dot{\mathcal{F}} = \mathcal{F},\ \dot{B} = B,\ \dot{U} = U \quad \}\ if\ k = 1 \\ &\dot{Y} = \tilde{Y},\ \dot{X} = \tilde{X},\ \dot{\mathcal{F}} = \tilde{\mathcal{F}},\ \dot{B} = \tilde{B},\ \dot{U} = \tilde{U} \quad \}\ if\ k > 1 \end{aligned}$$

with the respective OLS estimators given by:

$$
\begin{array}{ll}
\hat{\dot{B}} = \hat{B},\ \hat{\dot{U}} = \hat{U},\ \hat{\dot{S}} = \hat{S},\ \hat{\dot{\Sigma}} = \hat{\Sigma} & \}\ if\ k = 1 \\
\hat{\dot{B}} = \hat{\tilde{B}},\ \hat{\dot{U}} = \hat{\tilde{U}},\ \hat{\dot{S}} = \hat{\tilde{S}},\ \hat{\dot{\Sigma}} = \hat{\tilde{\Sigma}} & \}\ if\ k > 1
\end{array}
$$

and

$$\hat{D} = \left[\hat{a},\ (\iota_q'\hat{b} - \iota_n')'\right]' \quad \forall\ k, \tag{1.20}$$

where $\hat{a}$ and $\hat{b}$ are OLS estimators as defined in (1.10).

1.3 Methodology

This section describes econometric methods used for zero-beta inference. The analysis relies on two different Hotelling statistics.

1.3.1 Beta Sensitivity

Beta sensitivity inference proceeds by testing the joint significance of cross-sectional factor loadings, formally defined in (1.11), using the following Hotelling statistic [Hotelling (1947)]:

$$\Lambda_j = \frac{e_k[j]'\hat{B}\hat{S}^{-1}\hat{B}'e_k[j]}{e_k[j]'(X'X)^{-1}e_k[j]}, \quad j \in \{2,\ \dots\ ,\ k\}. \tag{1.21}$$

Under the null hypothesis in (1.11), Λ_j follows F-distribution when errors are *i.i.d.* Gaussian:

$$\Lambda_j \frac{T - k - n + 1}{n} \sim F\left(n, d\right), \tag{1.22}$$

where $d = T - k - n + 1$.

Let $F_{n,d,\alpha}$ indicate an α-level critical point from the F-distribution and define $\Upsilon_j = \Lambda_j \frac{d}{n}$. Level-$\alpha$ statistical significance of the Hotelling test occurs provided that:

$$\Upsilon_j > F_{n,d,\alpha}. \tag{1.23}$$

Rejection of the null hypothesis (1.11) defined for cross-sectional factor loadings implies that factor betas are jointly statistically different from zero.

The Hotelling statistic Λ_j is reliable for inference even in small sample with the size of the test being fully controlled and allows to test significance of factor betas jointly in cross-section.

1.3.2 Beta Pricing

Identification-robust confidence sets

Our beta pricing analysis relies on the method of Beaulieu, Dufour and Khalaf (2013). The latter involves the following Hotelling statistic defined for the ZBM restriction in (1.19):

$$\Lambda\left(\gamma_0\right) = \frac{(1,\gamma_0)\hat{D}\hat{\hat{\Sigma}}^{-1}\hat{D}'(1,\gamma_0)'}{1+[(\hat{\mu}-\gamma_0)^2/\hat{\sigma}^2]}, \tag{1.24}$$

$$\hat{\mu} = \frac{\sum_{t=1}^{T}\dot{\mathcal{F}}_t}{T}, \quad \hat{\sigma}^2 = \frac{\sum_{t=1}^{T}(\dot{\mathcal{F}}_t-\hat{\mu})^2}{T}.$$

Denote by $\underline{\gamma}_0$ a known value of γ_0 and let $F\left(n,d\right)$ indicate a Fisher distribution with n and d degrees of freedom. Provided that disturbances are *i.i.d.* jointly multivariate normal and the restriction (1.19) holds, it is the case that:

$$\Lambda\left(\underline{\gamma}_0\right)\frac{T-\dot{m}-n+1}{n} \sim F\left(n,d\right), \tag{1.25}$$

where $\dot{m}=k$ in a single-factor setting or $\dot{m}=q-1+\tilde{k}$ for a multifactor specification.

An identification-robust confidence set for γ_0 is constructed by inverting the Hotelling test in (1.25) at a significance level α using the method of Beaulieu, Dufour and Khalaf (2013, RES). In particular, for each value of $\underline{\gamma}_0$, the associated value of the test statistic $\Phi(\underline{\gamma}_0)=\Lambda(\underline{\gamma}_0)\frac{d}{n}$ is computed and compared to the the α-level critical point $F\left(n,d\right)$ from a Fisher distribution. Retaining all the values of $\underline{\gamma}_0$ for which $\Phi(\underline{\gamma}_0)$ is less or equal to the critical point produces an α-level confidence set for γ_0, denoted as $CS_\alpha(\gamma_0)$. Formally, test inversion yields a confidence set for γ_0 as a solution to the following inequality:

$$\Lambda\left(\underline{\gamma}_0\right)\frac{d}{n} \leq F_{n,d,\alpha}, \quad d=T-\dot{m}-n+1. \tag{1.26}$$

Appendix B reproduces the procedure for solving this inequality analytically.

Depending on the parameter identification strength and the fit of a model, there are four possibilities for the form of a robust confidence set, $CS_\alpha(\gamma_0)$: (1) a bounded interval results if the parameter is fully recoverable, which occurs in the absence of identification problems; (2) a real line is obtained when parameter identification completely fails due to insufficient information in the data; (3) the union of two unbounded sets results when identification strength is weak as information in the data is only partially informative for parameter recovery; (4) an empty set arises if a rejection of the model occurs for any admissible parameter value.

The confidence set produced this way for γ_0 is exact and identification-robust. This results as the method ensures the $(1-\alpha)$ confidence level for the probability of parameter inclusion irrespective of the identification strength and the number of observations the sample.

Wald-type confidence sets

There exist an alternative Wald-type method to construct a conventional confidence interval for γ_0. In particular, asymptotic maximum likelihood (ML) estimators are available in the literature for computing the zero-beta rate and its variance (Campbell, Lo and MacKinlay, 1997, Chapter 5, equation 5.3.81). These can be used to construct bounded confidence sets as per usual: *estimate* $\pm$ *(asymptotic standard error)* $\times$ *(asymptotic critical point)*. However, when identification problems arise, the recovery of the zero-beta rate can be severely undermined under standard inference methods due to insufficient information in the data. Specifically, recovering γ_0 requires the sum of betas (across factors) to be jointly (in cross-section) sufficiently different from one. In the extreme case when factor loadings strictly sum to unity, the zero-beta rate disappears from the model and is not recoverable. When this occurs, any parameter value is consistent with the data and the appropriate solution for the zero-beta rate, in such a case, should be a confidence set that covers the entire real line. The latter is never the case for a traditional confidence set that is always confined to be a bounded interval, which could be highly misleading for inference when weak identification is present. In particular, the probability of parameter coverage is not adequately controlled and could be quite low in the Wald-type case when identification fails. In contrast, robust confidence set achieves parameter coverage with a probability controlled at the confidence level $(1-\alpha)$ for any sample size regardless of whether factor betas jointly sum to one in cross-section.

This paper also reports Wald-type confidence sets estimated for the zero-beta rate using formulas for *ML* estimator and its Wald-type variance from Campbell, Lo and MacKinlay (1997) and restated for convenience in the Appendix C.

1.4 Data

Empirical analysis in this paper covers the study period between 11/2004 - 12/2015 and proceeds using the following monthly data. Estimation relies on real returns for 7 CBMFs listed in Table 1.1. These are obtained as follows. Prices on CBMFs are retrieved from Bloomberg. To have all prices in the same currency, series expressed in Euros or Swiss Franks are converted into US dollars using respectively DEXUSEU and DEXSZUS exchange rate series from the website for the Federal Reserve Economic Data (FRED). Real returns are then computed as $[ln(p_t) - ln(p_{t-1})] - \pi_t$, where p_t and p_{t-1} are CBMFs' prices in US dollars at time t and t-1 respectively and π_t is the US inflation rate at time t. The latter is based on the seasonally-adjusted US CPI series less food and energy (CPILFESL) obtained from FRED. Figures 1.1 and 1.2 display time series of real returns on CBMFs over the study period.

Returns for all factors are expressed in real terms (over the US CPI-based inflation rate), except for the returns on the mimicking portfolios. Those are obtained through a regression of the non-tradable factors on the real returns for base assets. The latter are given by the value-weighted returns on 6 stock portfolios (size/book-to-market value) and the momentum factor as suggested by Adrian, Etula and Tyler (2014). Data for base assets comes from the Kenneth French Data Library. US Treasury 10-year government bond yield (ticker USGG10YR) retrieved from Bloomberg is used as an additional base asset. Appendix D describes the procedure for constructing the mimicking portfolios.

As a benchmark for the stock market, we use the equity portfolio covering NYSE, AMEX and Nasdaq stocks. The analysis relies on the the value-weighted return (ticker VWRETD) for the latter portfolio retrieved from the Center for Research in Security Prices (CRSP) and expressed in excess of the inflation rate. As a proxy for the corporate bond market, Bank of America Merrill Lynch US High Yield Total Return Index (BAMLHYH0A0HYM2TRIV) is used with data obtained from FRED. To benchmark US Treasury and CMBS markets, we use data on respectively Bloomberg Barclays US treasury total return index (LUATTRUU) and Bloomberg Barclays CMBS Investment grade Total return index (LC09TRUU) both retrieved from Bloomberg. For the corporate bond, government bond and CMBS indices, real returns are computed as $[ln(I_t) - ln(I_{t-1})] - \pi_t$ where I_t and I_{t-1} are index values at time t and t-1 respectively.

Data on Fama-French HML and SMB factors comes from the online Kenneth French Data Library. DEF factor is computed as an excess Moody's seasoned Baa corporate bond yield over its Aaa counterpart both downloaded from FRED. TERM factor obtains by subtracting 1-month Treasury constant maturity rate from its 10-year counterpart (DGS1MO and DGS10 respectively) obtained from FRED (see Fama and French, 1993).

Time series for the traded liquidity factor of Pástor and Stambaugh (2003) are downloaded from the website of Lubos Pastor. Data for the funding liquidity factor of Fontaine and Garcia (2012) is retrieved from the website of Jean-Sébastien Fontaine.

For the estimation of Cummins and Weiss (2009) model, the corporate bond real return is based on the Bank of America Merrill Lynch US Corp BBB Total Return Index (BAMLCC0A4BBBTRIV) obtained from FRED. Also, the Moody's seasoned Baa corporate bond yield from FRED is used to compute the natural logarithm of the corporate bond yield used in the model.

1.5 Empirical Assessment

1.5.1 Descriptive Statistics

This section describes the data in terms of sample moments and presents results of the Normality test. Estimates are provided over the full sample between 11/2004 - 12/2015 and for sub-periods before, during and after the 2007-09 US recession.

Table 1.3 reports estimates of sample mean, variance, skewness and kurtosis for real returns on CBMFs and factors. Rows 1 through 7 provide observations for CBMFs. Results for factors are available in the following rows. Over the entire period between 11/2004 - 12/2015, most CBMFs display positive mean returns and tend to be similar in terms of variability. There is some heterogeneity among funds in terms of skewness and kurtosis. In particular, while some funds are considerably skewed to the left, others show only a negligible degree of skewness. Kurtosis is found to be elevated for all CBMFs and is more pronounced for a few funds. Sub-period estimates indicate that sample moments for CBMFs varied considerably over time. Specifically, funds performed best in terms of average returns and variance before the economic downturn. Mean returns are all positive before the recession and turn negative for almost every fund at a time of the economic turmoil. During the recovery period, most CBMFs regain positive mean returns and become less volatile than during the crisis, but overall tend to perform subpar compared to the pre-recession period. In terms of the third sample moment, few funds displayed positive skewness before and during the recession with most CBMFs being left skewed. Post-crisis, however, skewness estimates become negative for all CBMFs. Results for kurtosis are also interesting. Before the recession, most funds have kurtosis readings under 3 indicating thinner distribution tails than in Gaussian case. This starts to change during the period of economic instability when excess kurtosis becomes positive for returns on most funds. Following the recession, returns on all CBMFs become leptokurtic.

Sample moments estimated for the real returns on stock, corporate bond, government bond and CMBS benchmarks are displayed in Table 1.3, rows 8 through 11. Over the full sample, all benchmarks deliver positive mean returns which are higher for corporate bonds and equities. The stock return is the most volatile, while the government bond return is the most stable. The latter is also the only benchmark that is positively skewed. In addition, while estimates imply that all benchmarks are leptokurtic, the government bond return has the lowest reading for a positive excess kurtosis. For the corporate bond and CMBS benchmarks leptokurtic features are the most pronounced. There is some variation in results for these benchmarks across sub-samples. Before the recession, mean returns are positive for all benchmarks with stocks outperforming other markets. During the downturn, however, stocks perform the worst and mean returns are negative on every benchmark except for the government bonds. Returns on the latter actually improve between the first two periods. After the recession, mean returns on all benchmarks are positive again and even exceed their pre-crisis levels for stocks, corporate bonds and CMBS. In terms of variance, stock return is the most volatile with other benchmarks displaying the same degree of variability in the first sub-sample. Volatility for all benchmarks becomes elevated during the recession. Returns for all markets become more stable during the recovery period. For government bond and CMBS returns, variance declines to its pre-crisis levels. Negative skewness observed for stock and corporate bond returns in all periods gradually subsides over time. For government bonds, skewness is initially positive but turns negative after the crisis. The opposite trend emerges for CBMS. For the latter, there is a reversal from negative to positive skewness between the last two sub-periods. Excess kurtosis is negative for the stock return before and during the recession and almost vanishes during the recovery period with the reading of 3.03. CMBS return switches from negative to positive kurtosis between the first two sub-periods and becomes even more leptokurtic after the crisis. For the corporate bond benchmark, kurtosis estimate is always above 3 and is the largest during the crisis. Excess kurtosis for the government bond return goes from negative to positive between the first two sub-periods and is close to zero post-recession.

Summary statistics for the mimicking portfolios constructed for squared real returns on stock, corporate bond, government bond and CMBS benchmarks is available in Table 1.3, rows 12 thorough 15. Full-sample results indicate positive mean returns for all mimicking portfolios except the one for the corporate bonds. Across markets, returns on mimicking portfolios are broadly similar in terms of variance, skewness and kurtosis. All portfolio returns display moderate degree of negative skewness and positive excess kurtosis. Sub-sample analysis indicates that returns on all mimicking portfolios tend to become more volatile over time with variances that rise across sub-periods. Mean portfolio returns remain positive in all sub-periods. Moderate levels of skewness and excess kurtosis are detected for portfolio returns across all markets in every sub-period.

Table 1.3 also reports results for HML, SMB, TERM, DEF and the momentum factors in rows 16 through 20 respectively. Over the full sample, mean returns are positive for TERM, DEF and the momentum factors and negative for HML and SMB. Fixed income factors TERM and DEF are the least volatile, while momentum factor varies the most. All factors display a positive excess kurtosis with HML and the momentum factor being the most leptokurtic. HML and SMB are moderately skewed to the right. Positive skewness is more pronounced for DEF factor. TERM and MOM factors are negatively skewed. Split-sample results show that mean returns on TERM and DEF factors are always positive and are higher during and after the recession than before. Mean momentum return starts off positive, dips below zero during the recession and retraces back into positive territory thereafter. HML has negative mean return throughout that declines over time. Mean return for SMB is positive during the recession and below zero before and after. Variance for all factors tends to increase throughout the recession and then subsides during the recovery period. Momentum is skewed to the left in all sub-periods and has somewhat elevated degree of excess kurtosis during and after the recession. There is moderate level of positive skewness for all factors during and after the downturn.

Results for the mimicking portfolio for the funding liquidity factor of Fontaine and Garcia (2012), $M\Delta FL$, and the traded liquidity factor of Pástor and Stambaugh (2003), $LIQT$, are provided in Table 1.3, rows 21 and 22 respectively. Full-sample estimates indicate that mean returns are positive for both factors and are higher for $M\Delta FL$. Notably, mean return on $M\Delta FL$ varies more than that for any other factor over the full sample. Both factors are moderately skewed to the right and display considerable degree of positive excess kurtosis. Sub-sample results indicate that mean return on $M\Delta FL$ remains positive throughout rising during the downturn and falling thereafter below the pre-recession level. Interestingly, variance of $M\Delta FL$ jumps during the recession and is the highest across the factors in that sub-period. Volatility of the funding liquidity factor subsides considerably during the recovery period. $M\Delta FL$ also displays a moderate degree of excess kurtosis, which is negative during the times of financial stress and positive under normal financial conditions. For $LIQT$, variance rises somewhat during the recession and declines thereafter to its pre-crisis level. During normal times, $LIQT$ is somewhat negatively skewed, but displays skewness to the right at the time of the downturn. Mild excess kurtosis observed for $LIQT$ switches from negative to positive between the first two sub-periods and remains above zero thereafter.

Table 1.3 provides results for the corporate bond return and the natural logarithm of the corporate bond yield used in the model of Cummins and Weiss (2009) in the last two rows. Corporate bond return displays positive mean, negative skewness and considerable degree of positive excess kurtosis over the full sample. Returns are on average positive and left-skewed in all sub-periods. During the recession, volatility, skewness and kurtosis become more pronounced and mean value declines for the corporate bond return. Corporate bond yield, expressed in log form, has negative value over the full sample and in all sub-periods. This factor displays high volatility and mild positive skewness during and after the recession and in full sample. Also, there is positive excess kurtosis on the yield factor in all cases.

Tables 1.4 and 1.5 display correlation coefficients for the real returns on CBMFs and factors over the entire sample and in sub-periods. Over the full study period, correlation estimates obtained for different pairs of CBMFs are all positive and vary considerably across funds ranging between 0.1110 and 0.9996. Similar trend emerges in all sub-samples with a pronounced variability in correlations persisting over time. Aside from two CBMFs that display negative relationship during the recession, all mutual funds remain to be positively correlated in all sub-periods.

Split-sample and full-period analyses provide evidence of a positive relationship between stock, corporate bond and CMBS benchmarks with all CBMFs, which becomes more pronounced during the recession. Results are mixed for to the US treasury benchmark. Correlations of CBMFs with the latter are mostly positive before and during the recession and over the full sample. This is reversed during the recovery period, when the relation of the government bond benchmark becomes negative with most of CBMFs.

Over the full sample, there is a positive relationship between most CBMFs and portfolios mimicking for the squared return on stock, corporate bond, government bond and CMBS benchmarks. During the recession, correlation between these benchmarks and most CBMFs tends to be negative. Before the recession, CMBS and government bond markets are always positively related with CBMFs, while stock and corporate bond benchmarks tend to have negative correlations. After the downturn, correlations are always positive for stock, corporate bond and CMBS, but negative relative to the government bond market.

Returns on the mimicking portfolio for the differenced funding liquidity factor of Fontaine and Garcia (2012) tend to be correlated positively with most CBMFs' returns over the full sample and under stable financial conditions. During the period of extreme financial stress, however, the relationship becomes negative and more pronounced. Results are broadly similar for the traded liquidity factor of Pástor and Stambaugh (2003).

The relationship of CBMFs with SMB tends to be positive in all sub-periods and over the full sample. It becomes more pronounced during the recession. The dynamics between CBMFs and HML changes from negative to positive during the recession. This persists during the recovery period and dominates over the full sample.

Correlations with TERM are negative before the recession. The inverse relation tends to be amplified as financial markets become unstable. Once financial instability subsides, relationship with TERM becomes positive for most CBMFs. Over the full sample, however, negative dynamics prevails. For DEF factor, negative correlations switch to positive relative to most CMBFs as economy heads into a recession. This positive association becomes even stronger during the recovery period. Over the entire horizon, however, negative relation dominates.

As the recession begins, there is a reversal from mostly positive to negative dynamics with the momentum factor, which continues into the recovery period. Negative association also prevails over the entire study period. Merrill Lynch US Corp BBB Total Return Index In all cases, pronounced positive relationship is evident with the Merrill Lynch BBB corporate bond return, which is used for the model of Cummins and Weiss (2009). This is amplified as the financial instability rises. Relative to the Moody's Baa corporate bond yield expressed in logs, the association with CBMFs is positive and pronounced before the recession. Correlations with this benchmark become negative during the period of severe financial stress and retrace back to positive territory thereafter. The dynamics with the yield factor tends to be positive over the full sample.

Overall, split-sample analysis indicates considerable variability in the performance of CBMFs and factors across sub-periods. Dynamics between mutual funds and with factors also differs considerably over the business cycle. These preliminary results underscore the importance of examining the zero-beta neutrality in the context of the 2008 financial crisis and the ensuing recession.

We also conduct the combined Goodness-of-Fit (CGF) test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013). The procedure allows to check whether the model in (1.1) has *i.i.d.* jointly multivariate normal disturbances. In particular, testing is based on a combined null hypothesis of skewness and kurtosis equal to their Gaussian counterparts. CGF test produces p-values used to assess a statistical significance of this null hypothesis. Appendix E reproduces the procedure for implementing the CGF test.

Table 1.6 displays estimated p-values for all models. Results are available for sub-periods and over the full sample. In all cases but one, estimated p-values are below 5% indicating a rejection of a normality for the errors. CGF test is not significant during the recession for the combined model with Fama-French and the momentum factors.

Despite the rejection of normality, results obtained in a Gaussian setting provide for a reliable inference on the zero-beta neutrality of CBMFs. In particular, simulation evidence reported by Beaulieu, Dufour and Khalaf (2018) indicate that the identification-robust method, which assumes Gaussian errors, performs well in terms of statistical precision regardless of whether the true error distribution is normal, Student-t or GARCH. Specifically, to construct identification-robust confidence set, test inversion relies on the cut-off point from a Fisher distribution when Gaussian errors are assumed. Simulation results show that using F-based critical value does not lead to an over-rejection of the underlying Hotelling test regardless of whether the true error distribution is normal or has fatter tails. Moreover, in addition to being size-correct, the identification-robust method is accurate in terms of power. As such, these simulation results provide grounds for using the identification-robust method with the F-based cut-off point for inference on the zero-beta neutrality of CBMFs. In chapter 3, we further examine the fit to the data on CBMFs of the Student-t distribution.

1.5.2 Multivariate Linear Regression Results

This section describes regression results and proceeds with the zero-beta inference. All reported confidence sets maintain 5% significance level.

For each model, beta pricing and sensitivity results are placed in the same table. Throughout, squared and curly brackets contain respectively identification-robust and conventional confidence sets. Numbers in round brackets correspond to Hotelling p-values.

Reported mean factor returns are not enclosed.

Beta pricing relies on mean factor returns for inference. These are assessed against the confidence set estimated for the zero-beta rate. In particular, there is a risk premium on a given factor if its mean return lies outside of the confidence set for the zero-beta rate.

For inference on the zero-beta performance, note that interpretation of robust confidence sets varies with their shape, which depend on the parameter identification strength and model fit. In particular, a bounded interval obtains when there are no identification problems. Confidence set is empty if data rejects every parameter value satisfying the model. This amounts to a complete rejection of a model. Real line results when identification fails completely due to the lack of information in the data. Unity of two disjoint sets arises if information in the data is sufficient for a partial parameter identification.

Tables 1.7 and 1.8 provide results from estimating a single-factor BCAPM for respectively stock (Panel A), corporate bond (Panel B), government bond (Panel A) and CMBS (Panel B) market benchmarks. Strong evidence emerges against zero-beta performance of CBMFs. In particular, beta risk is priced for stock, government bond and CMBS benchmarks before the 2007-09 US recession as their respective mean returns fall outside of the robust confidence set estimated for the zero-beta rate. It is of interest that this occurs despite joint insignificance of factor loadings for any of the benchmarks. Evidence of the risk premium is also present for stock, corporate bond and CMBS benchmarks during the economic downturn. At this time, stock betas are also jointly significant indicating considerable exposure to systematic risk. Post-recession and over the full sample, BCAPM is rejected for any benchmark as the robust confidence set is empty. In the unrestricted setting, however, estimated Hotelling p-values are below 5% for all benchmarks, except Government bond in full-sample. This indicates jointly significant betas and may suggest that behavior of CBMFs was inconsistent with zero-beta performance. Post-recession and over the entire study period, the difference between robust and conventional sets is quite prominent. While the robust set is empty, its conventional counterpart takes on its usual closed form. The latter is misleading for beta-pricing inference since no parameter value satisfying the model conforms with the data. Unlike conventional confidence interval, robust set informs on the model fit and allows to avoid spurious inference.

Estimates from a combined model with stock, corporate bond, government bond and CMBS benchmarks are available in Table 1.12. Joint estimation informs on the relative factor importance and facilitates a more comprehensive analysis. The multifactor model provides further evidence against a zero-beta relation of CBMFs vis-a-vis the financial markets. CMBS emerges as a dominant benchmark with statistically non-negligible betas in all periods and priced risk prior and during the recession. The link with the stock benchmark is also pronounced. In this regard, a risk premium is present in the first two sub-periods, and there are significant stock betas post-recession and over the full-sample. In the multifactor setting, relevance of the corporate bond and government bond benchmarks appears to diminish. In particular, the former is neither priced nor has significant betas in any period. The link with the government bond benchmark appears to subside over time as the Hotelling test on its betas is significant only before the recession and beta risk is never priced for this factor. Full-sample results also suggest that the relation with the government bond market overall tends to be neutral. Similar to BCAPM, the joint model is also rejected post-crisis and over the full sample as evidenced by the empty robust confidence set obtained for the zero-beta rate. In stark contrast, its conventional analog is tight, yet recall that available simulation evidence shows that it is unreliable in the sense that it undercovers true parameter values.

Lack of fit for BCAPM and the joint four-market model in some periods may be due to omission of an important factor. In particular, imposing linearity between CBMFs and financial market benchmarks could be too restrictive. It has been suggested that using a mimicking portfolio for the squared market return as an additional factor allows to account for the market coskewness risk (see, for instance, Barone-Adesi, Gagliardini and Urga, 2004). The latter could be relevant as investors may prefer to hold a portfolio with a positive market coskewness. QCAPM augments traditional BCAPM with a portfolio that mimics squared market return, which could account for non-linearity and market coskewness. This may improve model fit and inform on the relevance of the coskewness risk for the zero-beta performance of CBMFs.

Tables 1.9 and 1.10 report QCAPM results obtained respectively for stock (Panel A), corporate bond (Panel B), government bond (Panel A) and CMBS (Panel B) benchmarks. QCAPM results suggest that CBMFs were not zero-beta with respect to financial markets. Notably, there is strong evidence that coskewness is priced regardless of the benchmark considered. This is the case whenever the zero-beta rate is identified and occurs even though coskewness betas are insignificant. It appears that investors were increasingly concerned about the coskewness despite low risk exposure as reflected in small coskewness betas. In particular, coskewness risk premium arises for stock and corporate bond benchmarks in the first two sub-periods and for CMBS in the last two. Coskewness is also priced for government bond benchmark post-recession. Jointly significant coskewness betas are observed only for QCAPM with the government bond benchmark over the full sample. Traditional market beta risk is also relevant. In particular, stock and CMBS incur premium for traditional beta risk during and after the downturn, respectively. The Hotelling test for market betas is significant for stock, corporate bond and CMBS in the final sub-period and over the entire sample. The overall indication is that CMBFs were not neutral relative to financial markets. Estimated robust confidence sets extend to the entire real line or are empty in some cases. This reveals, respectively, identification problems or lack of fit for QCAPM. However, their conventional analogs are always bounded, providing no information on the model fit, and may lead to spurious inference when identification is inadequate. For the government bond and CMBS, augmenting model with the coskewness factor improves fit to the data as robust confidence set for the zero-beta rate is no longer empty post-recession. However, identification fails for these models in some periods with the real line resulting as a robust confidence set. In these cases, identification failure precludes inference on beta pricing. Moreover, even though QCAPM fits the data well in sub-sample analysis, over the entire study period this model is still rejected even for CMBS and government bond benchmarks. As such, our analysis proceeds with alternative model specifications, which may provide better fit and additional insights on the zero-beta performance of CMBFs.

Zero-beta neutrality of CBMFs may not hold due to the market-wide liquidity risk. To explore this, it is informative to estimate a BCAPM augmented with the Pástor and Stambaugh (2003) liquidity factor, LIQT. Fontaine, Garcia and Gungor (2016) find that the funding risk is priced for a wide range of assets. To assess if CBMFs remain zero-beta regardless of the funding risk, a BCAPM augmented with the funding liquidity factor of Fontaine and Garcia (2012) is estimated. More precisely, a mimicking portfolio for the 1st difference of this factor is used, MΔFL. Table 1.11 provides results for the two models with LIQT and MΔFL in Panels A and B respectively. In all periods, both models are well-identified. In terms of fit to the data, both models underperform in the final sub-period and over the full sample. This is evidenced by the empty robust confidence set, which obtains for the zero-beta rate. For the model with LIQT, the market benchmark appears to be more relevant. Specifically, the latter is priced before and during the recession. Market betas are also significant during the recovery period and over the full sample. Liquidity factor incurs risk premium only before the recession and its betas are negligible throughout. Interestingly, there is evidence of the funding risk premium before and during the recession. Also, the role of the market benchmark appears to be less pronounced for the model with MΔFL. In particular, the former is priced only during the downturn. Market betas remain significant post-recession and over the full-sample. Overall, both models offer evidence against the zero-beta neutrality of CBMFs.

Cummins and Weiss (2009) estimate three-factor model for CBMFs and report statistically significant relation with financial markets for the period before June 2008. As estimated coefficients are quite small, the authors argue that CBMFs were near zero-beta during the study period. We estimate their model using identification-robust methods for the sample that extends beyond 2008. Table 1.13 provides results for the three-factor model of Cummins and Weiss (2009) with excess returns on stock and corporate bond benchmarks and the natural logarithm of the corporate bond yield. The model is always identified and fits well in sub-sample analysis. Full-sample results indicate model rejection as robust confidence set estimated for the zero-beta rate is void. In all periods, there is evidence of a risk premium on the corporate bond yield. No other factor appears to be priced. Over the entire study period, betas on each factor are jointly significant as evidenced by small Hotelling p-values. For stock benchmark, this is also the case post-recession. Overall, sub-sample findings suggest that CMBFs were not zero-beta. This is reinforced by full-sample estimation. Relative to the analysis of Cummins and Weiss (2009), reported results are similar in terms of small factor betas in the first two sub-periods. In addition, however, identification-robust methods used in this study reveals presence of a risk premium for the corporate bond yield and provides evidence against zero-beta performance of CBMFs.

Table 1.14 provides results from the five-factor Fama-French model. The latter incorporates both stock and fixed-income benchmarks that could further inform on the zero-beta neutrality of CBMFs. Fama and French (1993) document importance of these five factors for equity and fixed-income returns. Our zero-beta analysis explores relevance of Fama-French benchmarks for the performance of CBMFs. The model fits well with the data in all periods as the estimated confidence set for the zero-beta rate is never empty. Identification problems arise only in the final sub-period as robust confidence set covers the entire real line during this time. Its conventional counterpart, however, remains closed despite identification failure and misleads one to infer that neither factor is priced post-recession. Evidence against the zero-beta neutrality of CBMFs emerges from the split-sample analysis. Specifically, both TERM and DEF factors incur risk premium during the recession. Default risk is also priced before the downturn, as is the traditional market beta risk. Even though identification failure precludes inference on beta pricing post-recession, jointly significant betas on the market benchmark and TERM factor indicate elevated risk exposure and serve to reject zero-beta neutrality of CBMFs. Estimates obtained for the full study period reinforce split-sample findings. In particular, every factor is priced and Hotelling test on betas for the market benchmark and TERM is significant.

Results for the Fama-French model with either momentum, market liquidity or funding liquidity factor are also interesting. These are respectively available in Tables 1.15, 1.17 and 1.16. All models have a good fit to the data as neither has an empty robust confidence set estimated for the zero-beta rate in any of the periods. As in the case of the original five-factor Fama-French model, its extended versions with the momentum and Pástor and Stambaugh (2003) liquidity factor are well-identified in all periods except after the recession. Identification failure during that period results in the robust confidence set that extends to the entire real line and prevents beta pricing inference. For the model with the funding liquidity factor of Fontaine and Garcia (2012), identification fails in the first and the last sub-periods, but becomes strong during the recession and over the full sample. Congruent with the original five-factor Fama-French specification, each augmented model provides evidence against the zero-beta neutrality of CBMFs. In particular, inference pertaining to Fama-French factors remains robust regardless of the factor that augments the extended model. In addition, funding liquidity emerges as a relevant factor for the zero-beta analysis of CBMFs. In particular, funding risk is priced in both periods when the zero-beta rate is identified: during the recession and over the full sample. Liquidity factor of Pástor and Stambaugh (2003) is also found to be priced before the recession. The role of momentum is also pronounced as persistence risk is priced over the full sample and momentum betas are jointly significant following the recession.

Overall, the analysis reveals strong evidence against zero-beta neutrality of CBMFs robust against different mimicking portfolios, markets and factors.

1.6 Conclusion

This paper formally examines whether CBMFs are zero-beta neutral vis-a-vis the financial markets. The analysis proceeds by testing the joint beta significance to inform on the risk exposure of CBMFs. This augments beta pricing inference on whether factor risk is priced. Together, the two tests allow for an in-depth zero-beta analysis filling the void in the literature on Catastrophe bonds and CBMFs. Beta pricing relies on the inference method that achieves robustness regardless of the parameter identification strength. Performance of CBMFs is assessed against BCAPM, QCAPM, Cummins-Weiss, Fama-French, extended Carhart specifications and models with Fontaine and Garcia (2012) and Pástor and Stambaugh (2003) liquidity factors. Multiple markets are considered individually and in a joint setting. Empirical findings are broadly similar across models and markets. The overall indication is that CBMFs fell short of achieving the zero-beta neutrality. In particular, many factors incur risk premiums and/or have significant betas. This occurs in sub-periods and over the full sample between 11/2004 - 12/2005. Factors capturing coskewness, funding liquidity, interest rate and default risks emerge as relevant. These results are new to the literature on CBMFs. Also, there is a pronounced relation with the stock, corporate bond and CMBS markets.

Estimates highlight the importance of using the robust econometric method for assessing CBMFs. Unlike their conventional analogs, robust confidence sets detect identification problems and signal their presence. This allowed to avoid spurious inference in several cases when identification failed.

Figures

Figure 1.1: Real returns on CBMFs between 11/2004 − 12/2015 (Panel A)

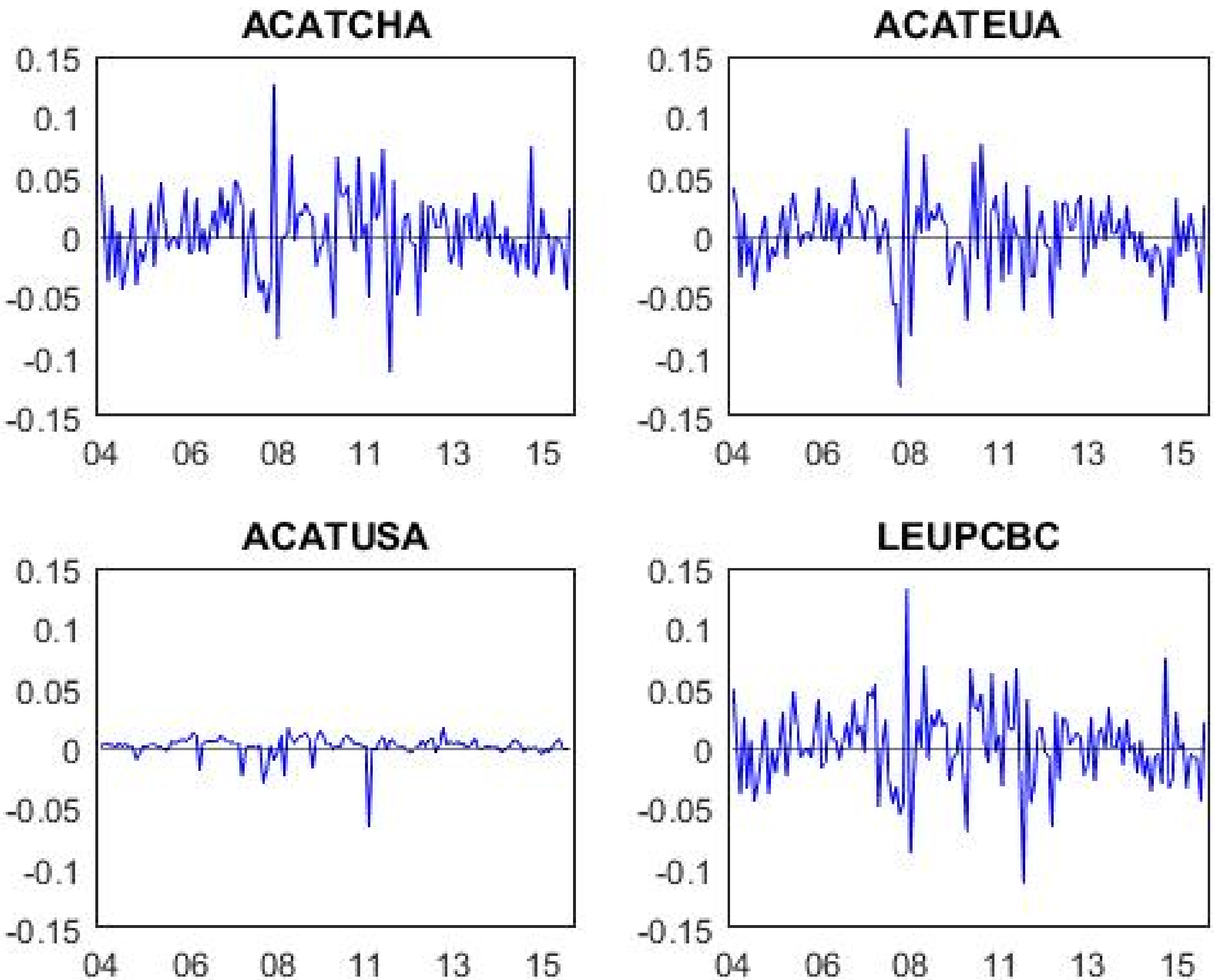
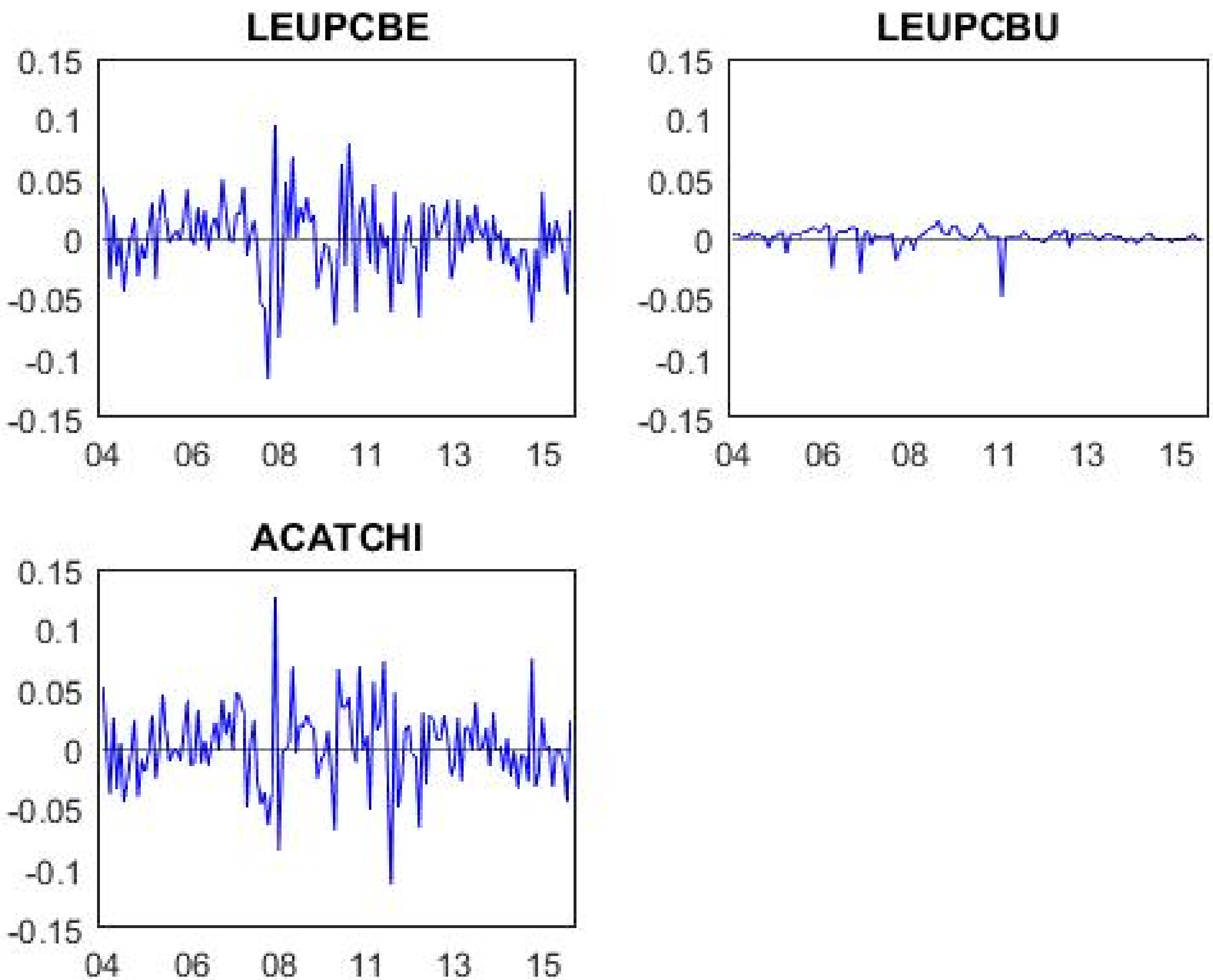


Figure 1.2: Real returns on CBMFs between 11/2004 − 12/2015 (Panel B)



Tables

Table 1.1: CBMFs

#	Bloomberg Ticker	Fund Name
1	ACATCHA	Falcon Cat Bond Fund Class A CHF
2	ACATEUA	Falcon Cat Bond Fund Class A EUR
3	ACATUSA	Falcon Cat Bond Fund Class A USD
4	ACATCHI	Falcon Cat Bond Fund Class I CHF
5	LEUPCBC	LGT CH Cat Bond Fund (CHF) A
6	LEUPCBE	LGT CH Cat Bond Fund (EUR) A
7	LEUPCBU	LGT CH Cat Bond Fund (USD) A

Table 1.2: Models

#	Model	Factors	# of Factors
1	CAPM: stock	R_{stock}	1
2	CAPM: corporate bond	R_{corp}	1
3	CAPM: govt bond	R_{govt}	1
4	CAPM: CMBS	R_{cmbs}	1
5	QCAPM: stock	R_{stock}, MR^2_{stock}	2
6	QCAPM: corporate bond	R_{corp}, MR^2_{corp}	2
7	QCAPM: govt bond	R_{govt}, MR^2_{govt}	2
8	QCAPM: CMBS	R_{cmbs}, MR^2_{cmbs}	2
9	Stock + Funding Liquidity	R_{stock}, $M\Delta FL$	2
10	Stock + Market Liquidity	R_{stock}, $LIQT$	2
11	Cummins and Weiss (2009)	R_{stock},R_{corp}, Y_{corp}	3
12	4-market model	R_{stock}, R_{corp}, R_{govt}, R_{cmbs}	4
13	Fama-French	R_{stock}, HML, SMB, TERM, DEF	5
14	Fama-French + Momentum	R_{stock}, HML, SMB, TERM, DEF, MOM	6
15	Fama-French + Funding Liquidity	R_{stock}, HML, SMB, TERM, DEF, $M\Delta FL$	6
16	Fama-French + Market Liquidity	R_{stock}, HML, SMB, TERM, DEF, $LIQT$	6

Note: All returns are expressed in excess of inflation (except for mimicking portfolios - those are constructed using excess base asset returns in deviation from inflation). R_{stock}, R_{corp}, R_{govt}, R_{cmbs} are excess returns on respectively stock, corporate bond, government bond and CMBS market indices; MR^2_{stock}, MR^2_{corp}, MR^2_{govt}, MR^2_{cmbs} are mimicking portfolios for the squared return on respectively stock, corporate bond, government bond and CMBS market indices; $M\Delta FL$ is a mimicking portfolio for the 1st difference of the funding liquidity factor proposed by Fontaine and Garcia (2012); Appendix C describes the procedure for constructing mimicking portfolios. $LIQT$ is a traded liquidity factor of Pástor and Stambaugh (2003); HML, SMB, TERM, DEF are Fama and French (1993) factors; MOM is a momentum factor; Y_{corp} is a logarithm of Moody's seasoned BAA corporate bond yield.

Table 1.3: Descriptive statistics

#	Variable	11/2004 - 11/2007				12/2007 - 06/2009				07/2009 - 12/2015				11/2004 - 12/2015			
		Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt
1	acatcha	0.002	0.02	0.07	2.36	-0.001	0.05	0.63	3.42	0.002	0.03	-0.42	4.42	0.001	0.03	0.02	4.61
2	acateua	0.005	0.02	-0.13	2.61	-0.004	0.05	-0.59	3.68	-0.002	0.03	-0.21	3.08	0.000	0.03	-0.56	4.77
3	acateusa	0.003	0.01	-1.63	7.55	-0.003	0.01	-0.88	2.71	0.002	0.01	-5.24	39.85	0.001	0.01	-3.91	27.21
4	leupcbc	0.003	0.02	-0.04	2.50	0.000	0.05	0.66	3.28	0.001	0.03	-0.45	4.48	0.002	0.03	0.08	4.88
5	leupcbe	0.005	0.02	-0.21	2.65	-0.004	0.05	-0.32	3.02	-0.003	0.03	-0.16	3.16	-0.001	0.03	-0.39	4.28
6	leupcbu	0.002	0.01	-2.52	9.31	-0.001	0.01	-1.30	4.11	0.001	0.01	-4.73	37.00	0.001	0.01	-3.42	21.46
7	acatchi	0.002	0.02	0.09	2.37	-0.001	0.05	0.62	3.40	0.002	0.03	-0.43	4.46	0.002	0.03	0.03	4.62
8	stock	0.009	0.03	-0.47	2.29	-0.021	0.07	-0.24	2.63	0.010	0.04	-0.13	3.03	0.005	0.04	-0.79	5.18
9	corp	0.003	0.01	-1.22	3.91	-0.004	0.06	-0.83	3.97	0.006	0.02	-0.06	3.57	0.004	0.03	-1.70	14.38
10	govt	0.002	0.01	0.10	2.40	0.003	0.02	0.62	3.44	0.001	0.01	-0.03	2.98	0.002	0.01	0.46	4.70
11	cmbs	0.001	0.01	-0.07	1.89	-0.009	0.07	-0.58	5.13	0.006	0.01	1.60	8.92	0.002	0.03	-2.01	27.42
12	stock2M	0.044	0.01	-0.42	2.73	0.063	0.02	0.51	2.60	0.047	0.09	0.50	3.71	0.004	0.03	-1.06	5.14
13	corp2M	0.029	0.02	-1.03	3.57	0.052	0.02	0.46	2.98	0.064	0.10	-0.01	3.58	-0.006	0.04	-0.92	4.57
14	govt2M	0.039	0.00	-1.11	4.94	0.034	0.01	-0.27	3.37	0.047	0.04	0.73	3.05	0.004	0.04	-1.22	7.46
15	cmbs2M	0.042	0.00	0.07	2.43	0.035	0.01	-0.53	3.37	0.028	0.01	0.62	4.47	0.008	0.04	-0.98	5.81
16	HML	-0.003	0.02	-0.82	4.28	-0.002	0.07	1.08	4.03	-0.002	0.02	0.64	3.95	-0.002	0.03	1.60	12.86
17	SMB	-0.003	0.02	0.62	3.26	0.006	0.03	1.40	6.11	-0.001	0.02	0.03	2.52	-0.001	0.02	0.71	4.98
18	TERM	0.004	0.01	0.59	2.54	0.024	0.01	0.13	2.93	0.023	0.01	0.46	2.33	0.018	0.01	-0.60	2.70
19	DEF	0.007	0.00	-1.03	3.62	0.019	0.01	0.35	1.53	0.009	0.00	0.17	2.53	0.010	0.01	2.47	9.63
20	MOM	0.004	0.02	-0.02	2.56	-0.015	0.10	-1.65	6.20	0.002	0.03	-0.35	4.17	0.000	0.05	-3.04	23.31
21	$M\Delta FL$	0.059	0.01	0.56	3.18	0.084	0.20	0.55	2.42	0.023	0.03	0.48	3.04	0.053	0.17	0.89	11.40
22	LIQT	0.009	0.03	-0.20	2.80	0.001	0.07	1.24	4.62	0.000	0.03	-0.14	3.51	0.003	0.04	0.86	7.79
23	corp - ML BBB	0.001	0.01	-0.26	2.03	0.000	0.04	-1.53	6.06	0.004	0.01	-0.03	3.20	0.003	0.02	-1.99	15.93
24	corp - Moody BAA	-2.793	0.04	-0.02	2.32	-2.603	0.11	0.32	1.90	-2.960	0.12	0.42	2.30	-2.863	0.16	0.37	2.92

Estimates for CBMF are reported in rows 1-7. *stock*, *stock2M*, *corp*, *corp2m*, *govt*, *govt2M*, *cmbs*, *cmbs2M* respectively are excess returns (above inflation) and mimicking portfolios on squared excess returns for stock, corporate bond, government bond, CMBS market indices. MOM is momentum and HML,SMB,TERM,DEF are Fama and French (1993) factors. $M\Delta FL$ is mimicking portfolio for (1st dif) Fontaine and Garcia (2012) funding liquidity factor. *LIQT* is Pástor and Stambaugh (2003) traded liquidity factor. corp - ML BBB is excess return on BofA Merrill Lynch US Corp BBB Total Return Index. corp - Moody BAA is logarithm of Moody's seasoned BAA corporate bond yield.

Table 1.4: Descriptive statistics - correlations

#	Variable	Before Recession: 11/2004 - 11/2007							During Recession: 12/2007 - 06/2009						
		acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi
1	acatcha	1							1						
2	acateua	0.9533	1						0.8833	1					
3	acatusa	0.2837	0.3182	1					0.1274	0.2501	1				
4	leupcbc	0.9850	0.9402	0.1642	1				0.9825	0.8570	-0.0229	1			
5	leupcbe	0.9280	0.9790	0.2731	0.9350	1			0.8695	0.9764	0.1013	0.8819	1		
6	leupcbu	0.1278	0.1858	0.6161	0.0986	0.3042	1		0.3326	0.4790	0.4564	0.3289	0.5179	1	
7	acatchi	0.9985	0.9493	0.2847	0.9843	0.9242	0.1276	1	0.9999	0.8821	0.1247	0.9831	0.8692	0.3339	1
8	stock	0.0608	0.1809	0.1016	0.0772	0.2405	0.3253	0.0603	0.3686	0.5915	0.2551	0.3935	0.6275	0.5832	0.3658
9	corp	0.1251	0.2198	0.2599	0.1361	0.2600	0.3694	0.1263	0.4073	0.5743	0.3985	0.3896	0.5652	0.6315	0.4054
10	glong	0.1323	0.0710	0.3249	0.0805	0.0060	-0.0837	0.1467	0.3526	0.3553	-0.2112	0.3692	0.3800	-0.0273	0.3510
11	cmbs	0.1534	0.1260	0.3190	0.1324	0.1123	0.1426	0.1648	0.5840	0.5332	0.0050	0.6186	0.5730	0.4345	0.5824
12	stock2M	-0.0417	-0.0540	-0.1236	0.0158	-0.0210	0.0358	-0.0439	-0.3891	-0.5969	-0.1361	-0.4040	-0.6200	-0.6036	-0.3877
13	corp2M	-0.1138	-0.0589	-0.0673	-0.0639	-0.0004	0.1951	-0.1153	-0.3550	-0.5853	-0.0937	-0.3635	-0.5951	-0.5237	-0.3536
14	glong2M	0.0679	0.1854	0.0286	0.1299	0.2727	0.3752	0.0643	-0.1893	-0.2410	-0.0570	-0.1663	-0.2164	0.0258	-0.1865
15	cmbs2M	0.1078	0.1453	0.0273	0.1564	0.1633	0.0809	0.1041	-0.2108	-0.1887	0.1271	-0.2089	-0.1847	0.1505	-0.2092
16	HML	-0.1107	-0.1515	-0.2272	-0.0867	-0.1083	0.0200	-0.1083	0.2143	0.2595	0.1424	0.2366	0.2961	0.2428	0.2119
17	SMB	0.0327	0.0523	-0.0101	0.0389	0.0909	0.1375	0.0218	0.1562	0.1310	0.2545	0.1567	0.1402	0.2955	0.1558
18	TERM	-0.1634	-0.1816	-0.1639	-0.1894	-0.1677	-0.0105	-0.1574	-0.2896	-0.3269	-0.1078	-0.3011	-0.3338	-0.2655	-0.2909
19	DEF	-0.1321	-0.1032	-0.0614	-0.1040	-0.1141	-0.1175	-0.1213	0.0387	0.0432	-0.0415	0.0215	0.0201	-0.2018	0.0340
20	MOM	0.1021	0.1032	-0.1170	0.0981	0.0928	-0.1104	0.0979	-0.1738	-0.2239	-0.2291	-0.1807	-0.2388	-0.2369	-0.1698
21	$M\Delta FL$	0.1034	0.0723	0.0413	0.0842	0.0393	-0.1076	0.0936	-0.2177	-0.3569	-0.3600	-0.1953	-0.3391	-0.6028	-0.2166
22	LIQT	0.1627	0.1641	0.0669	0.1498	0.1687	0.1079	0.1633	-0.1963	-0.1367	0.2164	-0.2515	-0.2102	0.0399	-0.1921
23	corp - ML BBB	0.1462	0.1473	0.4402	0.1087	0.1249	0.2224	0.1629	0.4161	0.6733	0.5581	0.3490	0.6184	0.6631	0.4141
24	corp - Moody BAA	0.2732	0.3016	0.1849	0.2927	0.3223	0.1785	0.2771	-0.1072	-0.1009	-0.1050	-0.1142	-0.1095	-0.2974	-0.1116

Note: Estimates for CBMF are reported in rows 1-7. $stock$, $stock2M$, $corp$, $corp2m$, $govt$, $govt2M$, $cmbs$, $cmbs2M$ respectively are excess returns (above inflation) and mimicking portfolios on squared excess returns for stock, corporate bond, government bond, CMBS market indices. MOM is momentum and HML,SMB,TERM,DEF are Fama and French (1993) factors. $M\Delta FL$ is mimicking portfolio for (1st dif) Fontaine and Garcia (2012) funding liquidity factor. $LIQT$ is Pástor and Stambaugh (2003) traded liquidity factor. corp - ML BBB is excess return on BofA Merrill Lynch US Corp BBB Total Return Index. corp - Moody BAA is logarithm of Moody's seasoned BAA corporate bond yield.

Table 1.5: Descriptive statistics - correlations (continued)

#	**Variable**	**After Recession: 11/2004 - 11/2007**							**Full Sample: 12/2007 - 06/2009**						
		acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi
1	acatcha	1							1						
2	acateua	0.6462	1						0.7616	1					
3	acatusa	0.2385	0.2131	1					0.2132	0.2431	1				
4	leupcbc	0.9935	0.6476	0.1685	1				0.9877	0.7566	0.1110	1			
5	leupcbe	0.6251	0.9911	0.1311	0.6402	1			0.7433	0.9844	0.1466	0.7620	1		
6	leupcbu	0.1959	0.2247	0.9074	0.1596	0.1839	1		0.1967	0.2580	0.7224	0.1700	0.2705	1	
7	acatchi	0.9997	0.6473	0.2382	0.9931	0.6262	0.1948	1	0.9996	0.7612	0.2118	0.9876	0.7432	0.1960	1
8	stock	0.3896	0.5584	0.0281	0.4051	0.5683	0.1081	0.3861	0.3373	0.5167	0.1491	0.3529	0.5388	0.2547	0.3341
9	corp	0.4893	0.4707	0.1484	0.5064	0.4811	0.1995	0.4861	0.3854	0.4668	0.2614	0.3865	0.4708	0.3022	0.3836
10	glong	-0.0436	-0.2725	0.0221	-0.0255	-0.2574	0.0990	-0.0398	0.1187	0.0088	-0.0138	0.1314	0.0186	0.0143	0.1228
11	cmbs	0.3376	0.2352	0.2918	0.3610	0.2470	0.3551	0.3344	0.3947	0.3477	0.1228	0.4262	0.3734	0.2429	0.3942
12	stock2M	0.3818	0.4308	0.0298	0.4047	0.4494	0.0744	0.3823	0.1449	0.2994	0.0708	0.1515	0.3138	0.1745	0.1421
13	corp2M	0.3352	0.3748	0.0830	0.3624	0.3924	0.1509	0.3353	0.1764	0.3441	0.0672	0.1790	0.3561	0.1641	0.1741
14	glong2M	-0.1583	-0.3996	-0.0583	-0.1491	-0.3877	-0.0649	-0.1554	0.1237	0.2609	-0.0111	0.1400	0.2805	0.1206	0.1211
15	cmbs2M	0.2141	0.2348	0.0952	0.2437	0.2532	0.2006	0.2114	0.1319	0.2796	0.0472	0.1396	0.2938	0.1392	0.1300
16	HML	0.1718	0.3042	0.1816	0.1599	0.2873	0.1564	0.1702	0.1506	0.2198	0.1130	0.1625	0.2355	0.1252	0.1492
17	SMB	0.0341	0.0194	0.0347	0.0298	0.0038	-0.0002	0.0326	0.0632	0.0477	0.0593	0.0651	0.0504	0.0723	0.0607
18	TERM	0.1173	0.0636	-0.0668	0.1456	0.0856	0.0231	0.1110	-0.0267	-0.1323	-0.1302	-0.0391	-0.1310	-0.0798	-0.0261
19	DEF	0.0482	0.0790	0.1251	0.0646	0.0935	0.2018	0.0466	-0.0041	-0.0210	-0.1167	0.0048	-0.0211	-0.0765	-0.0038
20	MOM	-0.2327	-0.2871	-0.2002	-0.2401	-0.2997	-0.2298	-0.2355	-0.1533	-0.1958	-0.1590	-0.1639	-0.2095	-0.1486	-0.1533
21	$M\Delta FL$	0.1073	0.1949	0.0632	0.0946	0.1847	-0.0013	0.1033	0.1925	0.2970	0.1420	0.2012	0.3111	0.1780	0.1903
22	LIQT	0.1677	0.1266	0.0172	0.1668	0.1283	0.0042	0.1732	0.0287	0.0360	0.0972	0.0007	0.0071	0.0397	0.0325
23	corp - ML BBB	0.3507	0.1548	0.1140	0.3722	0.1700	0.1783	0.3516	0.3401	0.3712	0.3144	0.3172	0.3533	0.2785	0.3419
24	corp - Moody BAA	0.1552	0.1086	0.0189	0.1884	0.1353	0.1457	0.1502	0.0376	0.0541	-0.0957	0.0701	0.0732	0.0043	0.0353

Note: Estimates for CBMF are reported in rows 1-7. $stock$, $stock2M$, $corp$, $corp2m$, $govt$, $govt2M$, $cmbs$, $cmbs2M$ respectively are excess returns (above inflation) and mimicking portfolios on squared excess returns for stock, corporate bond, government bond, CMBS market indices. MOM is momentum and HML,SMB,TERM,DEF are Fama and French (1993) factors. $M\Delta FL$ is mimicking portfolio for (1st dif) Fontaine and Garcia (2012) funding liquidity factor. $LIQT$ is Pástor and Stambaugh (2003) traded liquidity factor. corp - ML BBB is excess return on BofA Merrill Lynch US Corp BBB Total Return Index. corp - Moody BAA is logarithm of Moody's seasoned BAA corporate bond yield.

Table 1.6: Normality test

#	Model	Period			
		11/2004 - 11/2007	12/2007 - 06/2009	07/2009 - 12/2015	11/2004 - 12/2015
1	CAPM: stock	0.001	0.001	0.001	0.001
2	CAPM: corporate bond	0.001	0.001	0.001	0.001
3	CAPM: govt bond	0.001	0.001	0.001	0.001
4	CAPM: CMBS	0.001	0.001	0.001	0.001
5	QCAPM: stock	0.001	0.001	0.001	0.001
6	QCAPM: corporate bond	0.001	0.001	0.001	0.001
7	QCAPM: govt bond	0.001	0.001	0.001	0.001
8	QCAPM: CMBS	0.001	0.001	0.001	0.001
9	4-factors: stock, corp, govt, CMBS	0.001	0.016	0.001	0.001
10	Cummins and Weiss (2009)	0.001	0.001	0.001	0.001
11	Fama-French: Mkt, HML, SMB, TERM, DEF	0.001	0.001	0.001	0.001
12	Funding Liquidity ($M\Delta FL$) + Stock	0.001	0.001	0.001	0.001
13	Market Liquidity ($LIQT$) + Stock	0.001	0.001	0.001	0.001
14	Fama-French + Momentum	0.001	**0.088**	0.001	0.001
15	Fama-French + $M\Delta FL$	0.001	0.001	0.001	0.001
16	Fama-French + $LIQT$	0.001	0.015	0.001	0.001

Note: This table reports p-values for the Beaulieu, Dufour and Khalaf (2003, 2007, 2013) Combined Goodness-of-Fit (CGF) test for the case of normality. Under the null hypothesis, Gaussian values of skewness and kurtosis are tested for errors. CGF test is performed for models with a constant term.

Table 1.7: BCAPM (stocks and corporate bonds)

Period	Panel A: Stock			Panel B: Corporate bond		
11/2004 - 11/2007	[0.002, 0.005]	{0.002, 0.005}	**0.009***†	[0.003, 0.004]	{0.003, 0.005}	0.003
			(0.22)			(0.24)
12/2007 - 06/2009	[-0.003, 0.006]	{0.000, 0.003}	**-0.021***†	[-0.003, 0.004]	{-0.001, 0.002}	**-0.004***†
			(**0.02**)			(0.11)
07/2009 - 08/2014	∅	{-0.001, 0.002}	0.010†	∅	{-0.001, 0.002}	0.006†
			(**0.00**)			(**0.00**)
11/2004 - 12/2015	∅	{0.001, 0.003}	0.005†	∅	{0.001, 0.003}	0.004†
			(**0.00**)			(**0.00**)

Table 1.8: BCAPM (Treasuries and CMBS)

Period	Panel A: Government bond			Panel B: CMBS		
11/2004 - 11/2007	[0.003, 0.005]	{0.003, 0.005}	**0.002***†	[0.003, 0.006]	{0.003, 0.005}	**0.001***†
			(0.05)			(0.46)
12/2007 - 06/2009	[-0.002, 0.005]	{0.000, 0.003}	0.003	[-0.002, 0.005]	{0.000, 0.003}	**-0.009***†
			(0.58)			(0.11)
07/2009 - 08/2014	∅	{-0.001, 0.002}	0.001	∅	{-0.002, 0.001}	0.006†
			(**0.01**)			(**0.00**)
11/2004 - 12/2015	∅	{0.001, 0.003}	0.002	∅	{0.001, 0.003}	0.002
			(0.33)			(**0.00**)

Note: Identification-robust (conventional) confidence sets for the zero-beta rate, $CS(\gamma_0)$, are reported in squared (curly) brackets; Average excess returns (over inflation) are reported without brackets; round brackets are used for the Hotelling p-values. All factors and returns on Catastrophe bond mutual funds are in excess of inflation rate.

*, † denote statistically significant mean factor return that falls outside of respectively identification-robust and conventional confidence set at the 5% level. Beta pricing interprets mean factor returns against zero-beta confidence sets as follows: risk premium exists on a given factor if its mean return lies outside of $CS(\gamma_0)$.

Table 1.9: QCAPM (stocks and corporate bonds)

Period	Panel A: Stock				Panel B: Corporate bond			
	CS($\gamma_{\mathbf{0}}$)		Mkt	Mkt^2_{mim}	**CS**($\gamma_{\mathbf{0}}$)		Mkt	Mkt^2_{mim}
11/2004 - 11/2007	[-0.047, 0.009]	{-0.018, 0.006}	0.009†	**0.044***†	[-0.001, 0.008]	{0.001, 0.006}	0.003	**0.029***†
			(0.11)	(0.22)			(0.27)	(0.50)
12/2007 - 06/2009	[-0.009, 0.015]	{0.002, 0.010}	**-0.021***†	**0.063***†	[-0.009, 0.015]	{0.002, 0.011}	-0.004†	**0.052***†
			(0.21)	(0.46)			(0.51)	(0.28)
07/2009 - 12/2015	∅	{-0.001, 0.002}	0.010†	0.047†	∅	{-0.002, 0.002}	0.006†	0.064†
			(**0.00**)	(0.17)			(**0.03**)	(0.48)
11/2004 - 12/2015	∅	{0.001, 0.003}	0.005†	0.004†	∅	{0.001, 0.003}	0.004†	-0.006†
			(**0.00**)	(0.84)			(**0.00**)	(0.07)

Table 1.10: QCAPM (Treasuries and CMBS)

Period	Panel A: Government bond				Panel B: CMBS			
	CS($\gamma_{\mathbf{0}}$)		Mkt	Mkt^2_{mim}	**CS**($\gamma_{\mathbf{0}}$)		Mkt	Mkt^2_{mim}
11/2004 - 11/2007	$\mathbb{R}$	{-0.161, 0.043}	0.002	0.039	$\mathbb{R}$	{-0.046, 0.008}	0.001	0.042†
			(0.10)	(**0.03**)			(0.46)	(0.29)
12/2007 - 06/2009	$\mathbb{R}$	{-0.010, 0.010}	0.003	0.034†	[-0.123, 0.017]	{-0.008, 0.010}	-0.009†	**0.035***†
			(0.74)	(1.00)			(0.07)	(0.70)
07/2009 - 12/2015	[-0.001, 0.006]	{0.000, 0.004}	0.001	**0.047***†	[-0.006, 0.000]	{-0.007, 0.001}	**0.006***†	**0.028***†
			(0.10)	(0.10)			(**0.00**)	(0.42)
11/2004 - 12/2015	∅	{0.001, 0.003}	0.002	0.004†	∅	{0.001, 0.003}	0.002	0.008†
			(0.36)	(**0.03**)			(**0.00**)	(0.07)

Note: $CS(\gamma_0)$ denotes identification-robust (in squared brackets) and Wald-type (in curly brackets) confidence sets (CS) for the zero-beta rate, γ_0; Average excess (over inflation) return on each factor is reported without brackets; round brackets are used for the Hotelling p-values. Mkt is excess (over inflation) return on a given benchmark. Mkt^2_{mim} is the mimicking portfolio for the squared excess return on a given benchmark.

*, † denote statistically significant mean factor return that falls outside of respectively identification-robust and conventional confidence set at the 5% level. Beta pricing interprets mean factor returns against zero-beta confidence sets as follows: risk premium exists on a given factor if its mean return lies outside of $CS(\gamma_0)$.

Table 1.11: Models with liquidity factor

Period	Panel A: Mkt + Mkt Liquidity				Panel B: Mkt + Funding Liquidity			
	CS($\gamma_\mathbf{0}$)		Mkt	$LIQT$	**CS**($\gamma_\mathbf{0}$)		Mkt	$M\Delta FL$
11/2004 - 11/2007	[0.002, 0.005]	{0.002, 0.005}	**0.009***†	**0.009***†	[-0.021, 0.014]	{-0.005, 0.010}	0.009	**0.059***†
			(0.26)	(0.98)			(0.14)	(0.72)
12/2007 - 06/2009	[-0.003, 0.006]	{0.000, 0.003}	**-0.021***†	0.001	[-0.002, 0.006]	{0.000, 0.003}	**-0.021***†	**0.084***†
			(**0.03**)	(0.45)			(**0.04**)	(0.30)
07/2009 - 12/2015	∅	{-0.001, 0.002}	0.010†	0.000	∅	{-0.001, 0.003}	0.010†	0.023†
			(**0.00**)	(0.55)			(**0.00**)	(0.43)
11/2004 - 12/2015	∅	{0.001, 0.003}	0.005†	0.003	∅	{0.000, 0.003}	0.005†	0.053†
			(**0.00**)	(0.31)			(**0.00**)	(0.91)

Table 1.12: 4-market model

Period	**CS**($\gamma_\mathbf{0}$)		$stock$	$corp$	$govt$	$cmbs$
11/2004 - 11/2007	[0.002, 0.007]	{0.003, 0.005}	**0.009***†	0.003	0.002†	**0.001***†
			(0.69)	(0.73)	(**0.00**)	(**0.04**)
12/2007 - 06/2009	[-0.005, 0.007]	{-0.001, 0.003}	**-0.021***†	-0.004†	0.003	**-0.009***†
			(0.13)	(0.59)	(0.21)	(**0.02**)
07/2009 - 12/2015	∅	{-0.004, 0.000}	0.010†	0.006†	0.001†	0.006†
			(**0.01**)	(0.51)	(0.05)	(**0.00**)
11/2004 - 12/2015	∅	{0.001, 0.003}	0.005†	0.004†	0.002	0.002
			(**0.00**)	(0.12)	(0.14)	(**0.00**)

Note: $CS(\gamma_0)$ denotes identification-robust (squared brackets) and Wald-type (curly brackets) confidence sets for γ_0; Average excess (over inflation) returns are not enclosed; round brackets are used for the Hotelling p-values. Mkt indicates stock market benchmark; $LIQT$ is Pástor and Stambaugh (2003) traded liquidity factor; $M\Delta FL$ is a mimicking portfolio for Fontaine and Garcia (2012) funding liquidity factor; *stock*, *corp*, *govt*, *cmbs* are respectively stock, corporate bond, government bond, CMBS benchmarks. All factors and returns on Catastrophe bond mutual funds are expressed in deviation from inflation (for $M\Delta FL$, base asset returns are in excess of inflation).
*, † denote statistically significant mean factor return that falls outside of respectively identification-robust and conventional confidence set at the 5% level. Beta pricing interprets mean factor returns against zero-beta confidence sets as follows: risk premium exists on a given factor if its mean return lies outside of $CS(\gamma_0)$.

Table 1.13: Cummins & Weiss (2009) 3-factor model

Period	**CS**(γ_0)		*stock*	*corpr*	*corpy*
11/2004 - 11/2007	[-0.083, 0.261]	{-0.002, 0.161}	0.009	0.001	**-2.793***†
			(0.16)	(0.20)	(0.42)
12/2007 - 06/2009	[-0.151, 0.070]	{-0.076, -0.011}	-0.021	0.000†	**-2.603***†
			(0.18)	(0.05)	(0.63)
07/2009 - 12/2015	[-0.015, 0.091]	{0.001, 0.077}	0.010	0.004	**-2.960***†
			(**0.00**)	(0.05)	(0.09)
11/2004 - 12/2015	∅	{-0.001, 0.039}	0.005	0.003	**-2.863***†
			(**0.00**)	(**0.01**)	(**0.01**)

Note: $CS(\gamma_0)$ denotes identification-robust (in squared brackets) and Wald-type (in curly brackets) confidence sets (CS) for the zero-beta rate, γ_0; Average excess (over inflation) return on each factor is reported without brackets; round brackets are used for the Hotelling p-values. *stock*, *corpr*, *corpy* indicate respectively stock market benchmark, BofA Merrill Lynch US Corp BBB Total Index Return, and natural logarithm of Moody's seasoned BAA corporate bond yield.

*, † denote statistically significant mean factor return that falls outside of respectively identification-robust and conventional confidence set at the 5% level. Beta pricing interprets mean factor returns against zero-beta confidence sets as follows: risk premium exists on a given factor if its mean return lies outside of $CS(\gamma_0)$.

Table 1.14: Five-factor Fama-French model

Period	**CS**(γ_0)		Mkt	HML	SMB	$TERM$	DEF
11/2004 - 11/2007	[-0.025, 0.006]	{0.004, 0.006}	**0.009***†	-0.003†	-0.003†	0.004	**0.007***†
			(0.17)	(0.79)	(0.71)	(0.08)	(0.32)
12/2007 - 06/2009	[-0.063, 0.014]	{0.001, 0.009}	-0.021†	-0.002†	0.006	**0.024***†	**0.019***†
			(0.07)	(0.96)	(0.67)	(0.85)	(0.90)
07/2009 - 12/2015	$\mathbb{R}$	{-0.020, 0.130}	0.010	-0.002	-0.001	0.023	0.009
			(**0.00**)	(0.47)	(0.13)	(**0.03**)	(0.20)
11/2004 - 12/2015	[0.000, 0.004]	{0.001, 0.005}	**0.005***	**-0.002***†	**-0.001***†	**0.018***†	**0.010***†
			(**0.00**)	(0.43)	(0.24)	(**0.01**)	(0.36)

Table 1.15: Fama-French and Momentum

Period	**CS**(γ_0)		Mkt	HML	SMB	$TERM$	DEF	MOM
11/2004 - 11/2007	[-0.096, 0.006]	{0.004, 0.006}	**0.009***†	-0.003†	-0.003†	0.004	**0.007***†	0.004
			(0.19)	(0.75)	(0.78)	(0.14)	(0.32)	(0.89)
12/2007 - 06/2009	[-0.030, 0.011]	{0.004, 0.007}	-0.021†	-0.002†	0.006	**0.024***†	**0.019***†	-0.015†
			(0.12)	(0.22)	(0.89)	(0.89)	(0.27)	(0.24)
07/2009 - 12/2015	$\mathbb{R}$	{-0.175, 0.377}	0.010	-0.002	-0.001	0.023	0.009	0.002
			(**0.00**)	(0.05)	(0.18)	(**0.02**)	(0.15)	(**0.01**)
11/2004 - 12/2015	[0.002, 0.005]	{0.002, 0.005}	0.005	**-0.002***†	**-0.001***†	**0.018***†	**0.010***†	**0.000***†
			(**0.00**)	(0.94)	(0.24)	(**0.02**)	(0.09)	(0.13)

Note: $CS(\gamma_0)$ denotes identification-robust (in squared brackets) and Wald-type (in curly brackets) confidence sets (CS) for the zero-beta rate, γ_0; Average excess (over inflation) return on each factor is reported without brackets; round brackets are used for the Hotelling p-values. Mkt indicates stock market benchmark; HML, SMB, $TERM$, DEF are Fama and French (1993) factors; MOM is Carhart (1997) momentum factor. All factors and returns on Catastrophe bond mutual funds are expressed in deviation from inflation rate.

*, † denote statistically significant mean factor return that falls outside of respectively identification-robust and conventional confidence set at the 5% level. Beta pricing interprets mean factor returns against zero-beta confidence sets as follows: risk premium exists on a given factor if its mean return lies outside of $CS(\gamma_0)$.

Table 1.16: Fama-French and Funding Liquidity Factor of Fontaine and Garcia (2012)

Period	**CS**(γ_0)		Mkt	HML	SMB	$TERM$	DEF	$M\Delta FL$
11/2004 - 11/2007	$\mathbb{R}$	{0.001, 0.008}	0.009†	-0.003†	-0.003†	0.004	0.007	0.059†
			(0.08)	(0.81)	(0.52)	(0.12)	(0.44)	(0.72)
12/2007 - 06/2009	[-0.027, 0.013]	{0.004, 0.008}	-0.021†	-0.002†	0.006	**0.024***†	**0.019***†	**0.084***†
			(0.33)	(0.99)	(0.55)	(0.89)	(0.86)	(0.31)
07/2009 - 12/2015	$\mathbb{R}$	{0.010, 0.015}	0.010	-0.002†	-0.001†	0.023†	0.009†	0.023†
			(**0.00**)	(0.47)	(0.12)	(**0.02**)	(0.40)	(0.54)
11/2004 - 12/2015	[0.000, 0.005]	{0.001, 0.005}	0.005	**-0.002***†	**-0.001***†	**0.018***†	**0.010***†	**0.053***†
			(**0.00**)	(0.76)	(0.28)	(**0.01**)	(0.13)	(0.66)

Table 1.17: Fama-French and Traded Liquidity Factor of Pástor and Stambaugh (2003)

Period	**CS**(γ_0)		Mkt	HML	SMB	$TERM$	DEF	$LIQT$
11/2004 - 11/2007	[-0.075, 0.006]	{0.004, 0.006}	**0.009***†	-0.003†	-0.003†	0.004†	**0.007***†	**0.009***†
			(0.18)	(0.80)	(0.68)	(0.09)	(0.34)	(0.97)
12/2007 - 06/2009	[-0.329, 0.014]	{0.001, 0.008}	-0.021†	-0.002†	0.006	**0.024***†	**0.019***†	0.001
			(0.10)	(1.00)	(0.73)	(0.70)	(0.74)	(0.59)
07/2009 - 12/2015	$\mathbb{R}$	{0.001, 0.091}	0.010	-0.002†	-0.001†	0.023	0.009	0.000†
			(**0.00**)	(0.16)	(0.06)	(**0.01**)	(0.17)	(0.07)
11/2004 - 12/2015	[0.000, 0.004]	{0.001, 0.005}	**0.005***	**-0.002***†	**-0.001***†	**0.018***†	**0.010***†	0.003
			(**0.00**)	(0.54)	(0.18)	(**0.01**)	(0.36)	(0.27)

Note: $CS(\gamma_0)$ denotes identification-robust (in squared brackets) and Wald-type (in curly brackets) confidence sets (CS) for the zero-beta rate, γ_0; Average excess (over inflation) return on each factor is reported without brackets; round brackets are used for the Hotelling p-values. Mkt indicates stock market benchmark; HML, SMB, $TERM$, DEF are Fama and French (1993) factors; $M\Delta FL$ is a mimicking portfolio for Fontaine and Garcia (2012) funding liquidity factor; $LIQT$ is Pástor and Stambaugh (2003) traded liquidity factor. All factors and returns on Catastrophe bond mutual funds are expressed in deviation from inflation ($M\Delta FL$ is obtained via projection of the funding liquidity factor on base asset returns in excess of inflation).

*, † denote statistically significant mean factor return that falls outside of respectively identification-robust and conventional confidence set at the 5% level. Beta pricing interprets mean factor returns against zero-beta confidence sets as follows: risk premium exists on a given factor if its mean return lies outside of $CS(\gamma_0)$.

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Appendices 1

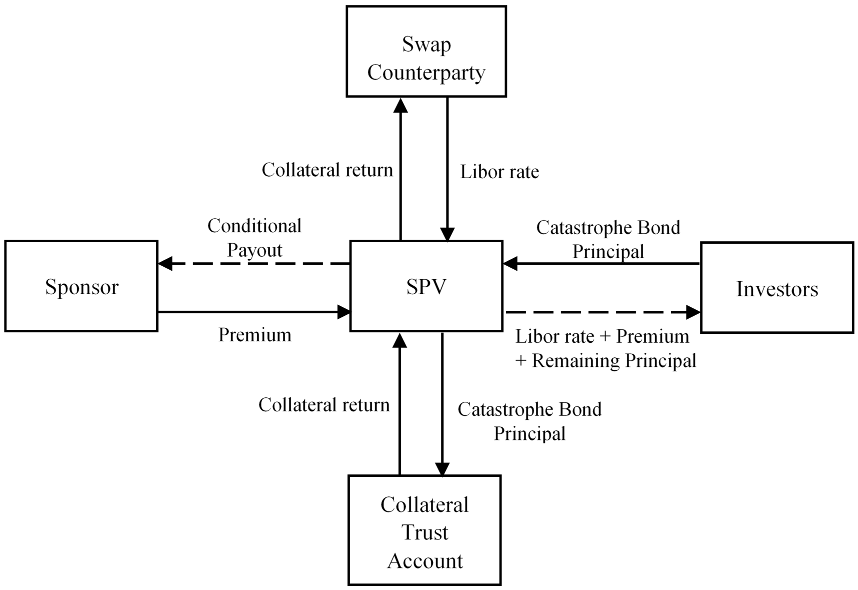
A Catastrophe Bonds

Private companies and national governments came to rely on Catastrophe bonds as a frequently used instrument for accessing capital in financial markets to fund catastrophe-triggered losses and disaster recovery efforts. From the perspective of a sponsoring party, usually a reinsurance company, corporation or a national government, these bonds provide an insurance that pays out in the event of a rare, high-impact natural disaster, like earthquake. For investors seeking a diversification, the low comovement between catastrophes and financial securities makes these bonds a welcome addition to a larger investment portfolio (Litzenberger, Beaglehole and Reynolds, 1996).

Although the market capitalization for Catastrophe bonds has already reached US $30 billion in 2017, these securities were launched only in mid-90s (Artemis, 2017). This rapid expansion is largely due to the importance of Catastrophe bonds for reinsurance markets as an alternative way to obtain risk coverage. Globally, nearly 30% of alternative funding for property catastrophe reinsurance is secured through Catastrophe bonds (Aon Benfield, 2017a).

In terms of its structure shown in Figure 1.A.1, a Catastrophe bond usually relies on a Special Purpose Vehicle (SPV) to facilitate an arrangement between a sponsor issuing the bond and investors in financial markets. In particular, the SPV signs a contract with a sponsor to accept a risk of catastrophe-triggered losses and issues bonds in financial markets to raise contingency funds for protection against the catastrophe risk. Capital obtained through the sale of Catastrophe bonds is used to create a collateral portfolio of highly-rated financial assets. For investors, payments on a Catastrophe bond consist of regular coupon payments (premium and a floating rate) that accrue for as long as the bond is outstanding and a final principal payout at maturity. Investors realize their bond payments unless a default-triggering catastrophe strikes. If the latter event occurs before the bond maturity, investors loose a portion or an entire amount of their bond payments, while the sponsoring party receives funds resulting from the sale of collateral assets that back the Catastrophe bond.

Figure 1.A.1: Catastrophe bond: structure



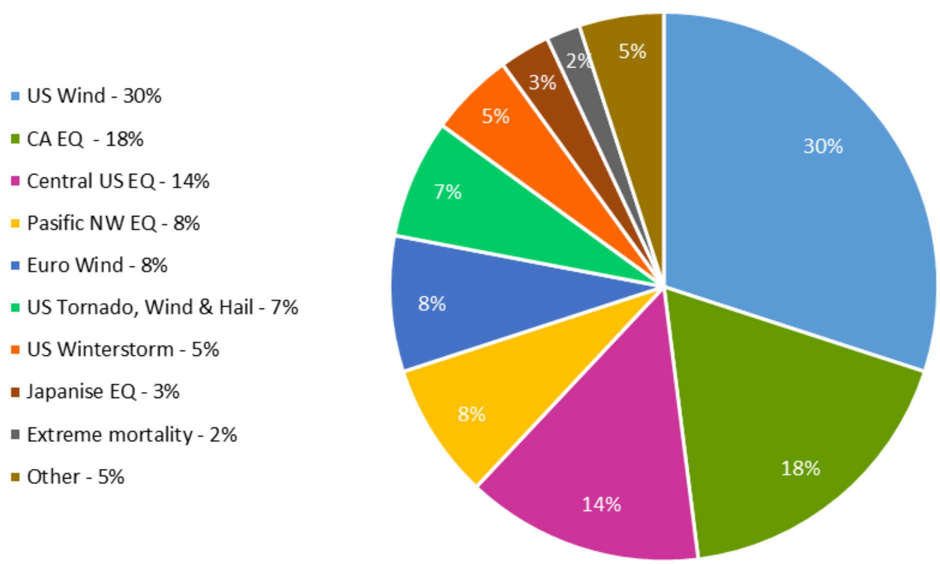
Before the 2007-08 financial crisis, most Catastrophe bonds also addressed their interest rate and collateral value risks though services of a Total Return Swap Counterparty (TRSC). For Catastrophe bonds that had Lehman Brothers as their TRSC, the bankruptcy of the investment bank in 2008 compounded the problems with collateral assets that these bonds incurred during the crisis and eventually led to their default. Since then, the use of the TRSC has been mostly avoided. Measures that have been used instead focus on enhanced collateral management including stricter criteria for selecting assets allowed as collateral, thorough monitoring of the collateral portfolio and regular investor updates.

Most Catastrophe bonds are sponsored by underwriters, although there have been numerous transactions initiated by government-affiliated entities (both at national and regional levels) and private institutions. While a Catastrophe bond is outstanding (and if no qualifying catastrophe occurs), sponsors pay a regular premium to investors, passed through the SPV as a portion of the coupon, to compensate investors for bearing the catastrophe risk.

For a Catastrophe bond to default, its trigger variable is required to surpass a certain limit. Both the trigger and the limit are chosen ex-ante and known at the time the bond is issued. Catastrophe bonds differ in terms of the variables used as triggers that can be broadly classified into five groups: (a) an indemnity trigger conditions default on the extent of sponsor's own losses; (b) an index trigger is contingent on an index that is not sponsor-specific; (c) a parametric trigger depends on characteristics of a disaster itself, e.g., the magnitude of an earthquake; (d) a model loss trigger references a variable resulting from a simulation; (e) a hybrid trigger uses multiple variables to determine if there is a default.

In terms of their coverage, Catastrophe bonds primarily focus on disasters that occur in the US. As can be seen from the Figure 1.A.2, 82% of all outstanding capital raised through Catastrophe bonds hedges US-based risks. In particular, coverage against the US earthquake risk in California, the Pacific Northwest and the central US represents respectively 18%, 8% and 14% of the overall capacity supported by Catastrophe bonds. Also, another 42% of the outstanding funds protect against windstorm and tornado risks in the US. The demand for coverage is lower for the European windstorm (8%) and Japanese earthquake (3%). Also, small portion of outstanding Catastrophe bonds hedges risks of extreme mortality (2%) and other events (5%).

Figure 1.A.2: Capacity by catastrophe/region (as of July 1, 2012)

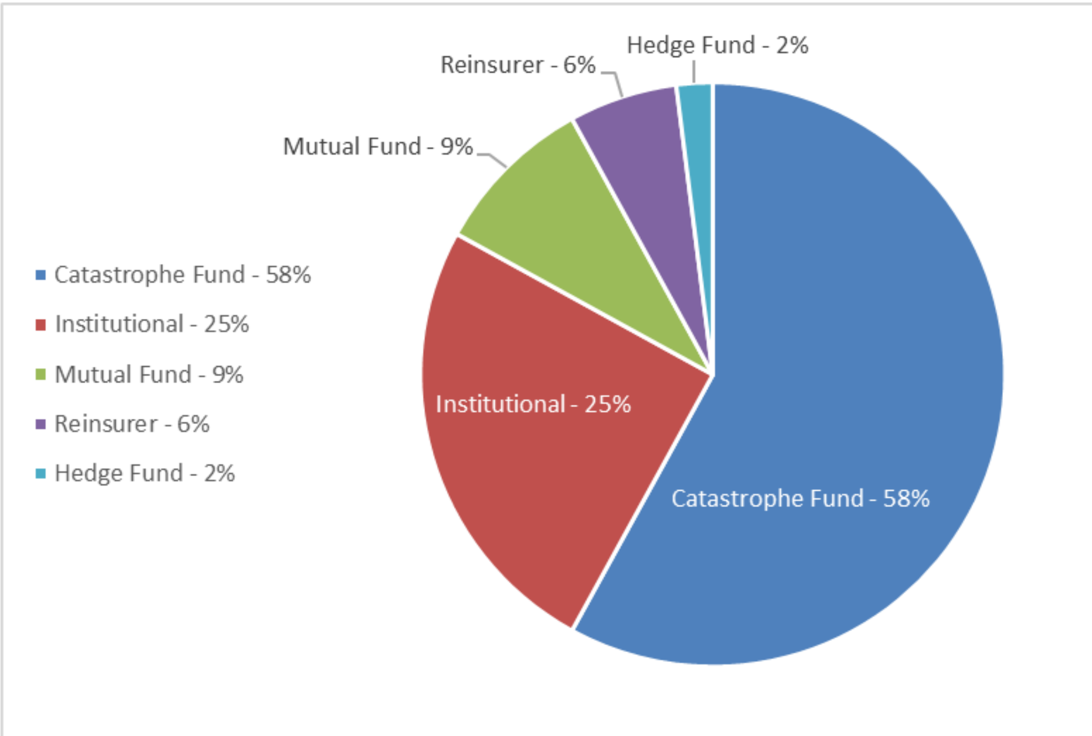


Source: Swiss Re (2012)– ILS Market Update, Vol. XVIII, July

To provide an example, we describe a four-year Catastrophe bond that was issued by Allstate Insurance Company in March 2018. The bond covers US (except New Jersey and Florida) storms, earthquake, severe weather, fire and other perils, is structured with an indemnity trigger and offers investors an interest spread of 5.5%. The USD $500 million transaction was implemented via an intermediary SPV entity, Sanders Re Ltd 2018-1 (see Artemis, 2018).

As the Figure 1.A.3 shows, the primary market for Catastrophe bonds mainly attracts investors from outside of the reinsurance sector. Dominating the market, CBMFs captured nearly 60% of all new bond issues over the year before mid-2017. In addition, institutional investors, mutual funds and hedge funds provided capital for 25%, 9% and 2% of newly-issued Catastrophe bonds. Only 6% of Catastrophe bonds were financed by reinsurance companies.

Figure 1.A.3: Catastrophe bond: investor base (12 months preceding June 30, 2017)



Source: Aon Benfield (2017b)– Insurance-Linked Securities. Alternative Capital Breaks new boundaries. September 2017 Report.

B Identification-robust confidence set

This appendix reproduces the procedure for assembling an exact, identification-robust confidence set for the zero-beta rate, $CS_\alpha(\gamma_0)$, with significance level α as proposed by Beaulieu, Dufour and Khalaf (2013).

The method performs an inversion of the Hotelling test defined in (1.26) under equations (1.18) and (1.19). These are restated below for convenience:

$$\dot{Y} = \dot{X}\dot{B} + \dot{U}, \tag{1.17}$$

$$H_0^{(2)}(\gamma_0) : (1, \gamma_0)D = 0, \quad D = \left[\alpha,\ (\iota_q'\beta - \iota_n')'\right]', \quad \textit{for some unknown } \gamma_0, \tag{1.18}$$

$$\Lambda\left(\underline{\gamma}_0\right)\frac{d}{n} \leq F_{n,d,\alpha}, \quad d = T - \dot{m} - n + 1, \tag{1.25}$$

where $\underline{\gamma}_0$ denotes a known value of γ_0 selected from an admissible set $\Gamma = \mathbb{R}$ and $\dot{m} = k$ in a single-factor setting or $\dot{m} = q - 1 + \tilde{k}$ for a multifactor specification.

$CS_\alpha(\gamma_0)$ is analytically derived as a solution to (1.26). Formally, confidence level of the set:

$$CS_\alpha(\gamma_0) = \{\gamma_0 \in \Gamma : \Lambda(\gamma_0)\frac{d}{n} \leq F_{n,d,\alpha}\}, \tag{B1}$$

is controlled at $(1-\alpha)$. That is, $CS_\alpha(\gamma_0)$ achieves parameter coverage with a probability of no less than $(1-\alpha)$.

With disturbances in (1.18) partitioned as $\dot{U} = \left[\dot{U}_1, \ \ldots \ , \dot{U}_n\right] = \left[\dot{V}_1, \ \ldots \ , \dot{V}_T\right]'$, test inversion involves the following distributional assumption on the errors given an unknown matrix J with a non-zero determinant:

$$V_t = JW_t, \quad t = 1, \ \ldots \ , \ T. \tag{B2}$$

Distribution of W_t may be known or could depend on an unknown parameter ρ. Results are exact when errors are jointly multivariate normal and *i.i.d.*:

$$W_t \sim_{i.i.d.} N(0, I_n), \tag{B3}$$

in the sense that the Hotelling test maintains correct size at a significance level α. Simulation evidence available in the literature shows that using F-distribution as an approximation performs well in a non-Gaussian setting see (Beaulieu, Dufour and Khalaf, 2018).

Solving for $CS_\alpha(\gamma_0)$ analytically requires rewriting the Hotelling test in (1.26) as follows:

$$P(\gamma_0) - \frac{F_\alpha}{T - \dot{m} - n + 1}G(\gamma_0) \leq F_{n,d,\alpha}, \tag{B4}$$

$$P(\gamma_0) = (\hat{\alpha} + \hat{\phi}\gamma_0)'\hat{\dot{\Sigma}}^{-1}(\hat{\alpha} + \hat{\phi}'\gamma_0) = \hat{\alpha}'\hat{\dot{\Sigma}}^{-1}\alpha + 2\hat{\phi}'\hat{\dot{\Sigma}}^{-1}\hat{\phi}\gamma_0 + \hat{\phi}'\hat{\dot{\Sigma}}^{-1}\hat{\phi}\gamma_0^2, \quad \phi = (\iota_q'\hat{\beta} - \iota_n')',$$

$$G(\gamma_0) = 1 + \frac{(\hat{\mu} - \gamma_0)^2}{\hat{\sigma}^2} = 1 + \frac{\hat{\mu}^2}{\hat{\sigma}^2} - 2\frac{\hat{\mu}}{\hat{\sigma}^2}\gamma_0 + \frac{1}{\hat{\sigma}^2}\gamma_0^2,$$

which is further restated in a quadratic form with a solution for $CS_\alpha(\gamma_0)$ given by:

$$CS_\alpha(\gamma_0) = \{\gamma_0 \in \Gamma : A\gamma_0^2 + B\gamma_0 + C \leq 0\}, \tag{B5}$$

The confidence set can be one of the following: (1) bounded interval, $[a, b]$; (2) union of two disjoint sets, $(-\infty, a] \cup [b, \infty)$; (3) real line, $\mathbb{R}$; (4) empty set, $\varnothing$.

C Conventional estimator of the zero-beta rate and its variance

Conventional point estimate for the zero-beta rate, $\hat{\gamma}_0$, is obtained using an analytical formula of Beaulieu, Dufour and Khalaf (2018) for the Maximum Likelihood estimator [**MLE**] of γ_0.

In particular, consider expressions (1.18) and (1.19) and divide $(\dot{k} \times \dot{k})$ matrix $(\dot{X}'\dot{X})^{-1}$ into segments as follows:

$$(\dot{X}'\dot{X})^{-1} = \begin{bmatrix} \dot{x}_{11} & \dot{x}_{12} \\ \dot{x}_{21} & \dot{x}_{22} \end{bmatrix},$$

where terms $\dot{x}_{22}$ and $\dot{x}_{21} = \dot{x}_{12}'$ are respectively $(\dot{q} \times \dot{q})$ and $(\dot{q} \times 1)$ with $\dot{k} = \dot{q} + 1$.

Further, let $\hat{\eta}$ denote the minimum non-zero root for:

$$Z(\dot{X}, \dot{Y}) = (\dot{X}'\dot{X})^{-1}\dot{X}'\dot{Y}\hat{\dot{\Sigma}}^{-1}\dot{Y}'\dot{X},$$

with $\hat{\dot{\Sigma}}$ denoting the OLS estimator for the model in (1.18).

Under (1.18) and (1.19), the MLE of γ_0 takes the form:

$$\hat{\gamma}_0 = -\left(\hat{\phi}\hat{\dot{\Sigma}}^{-1}\hat{\phi}' - \hat{\eta}\dot{x}_{22}\right)^{-1}\left(\hat{\phi}\hat{\dot{\Sigma}}^{-1}\hat{\alpha} - \hat{\eta}\dot{x}_{21}\right), \quad \hat{\phi} = (\iota_q'\hat{\beta} - \iota_n')',$$

where $\hat{\alpha}$ and $\hat{\beta}$ are OLS estimators of the intercept and slope coefficients in the model (1.8) given by (1.10).

Conventional asymptotic variance of $\hat{\gamma}_0$ is calculated using Wald-type estimator of Campbell, Lo and MacKinlay (1997, equation 6.2.27):

$$\hat{\sigma}^2_{\hat{\gamma}_0} = \frac{1}{T}\left[1 + (\hat{\mu}_q - \hat{\gamma}_0\iota_q)'\Phi_q^{-1}(\hat{\mu}_q - \hat{\gamma}_0\iota_q)\right]\left[(\iota_n - \hat{B}^*\iota_q)'\hat{\Sigma}^{*-1}(\iota_n - \hat{B}^*\iota_q)\right]^{-1},$$

such that

$$\hat{\mu}_q = \frac{\sum_{t=1}^T F_t}{T}, \quad \hat{\Phi}_q = \frac{\sum_{t=1}^T (F_t - \hat{\mu}_q)(F_t - \hat{\mu}_q)'}{T},$$

$$\hat{B}^* = \left[(y_t - \iota_n\hat{\gamma}_0)(F_t - \iota_q\hat{\gamma}_0)'\right]\left[(F_t - \iota_q\hat{\gamma}_0)(F_t - \iota_q\hat{\gamma}_0)'\right]^{-1},$$

$$\hat{\Sigma}^* = \frac{\sum_{t=1}^T \left[y_t - \iota_n\hat{\gamma}_0 - \hat{B}^*(F_t - \iota_q\hat{\gamma}_0)\right]\left[y_t - \iota_n\hat{\gamma}_0 - \hat{B}^*(F_t - \iota_q\hat{\gamma}_0)\right]'}{T},$$

where $(q \times 1)$ vector $F_t = (R_{1t}, ..., R_{qt})'$ denotes a t-th row of the $(T \times q)$ matrix $F = [R_1, ..., R_q] = [F_1, ..., F_T]'$ and $(n \times 1)$ vector $y_t = (y_{1t}, ..., y_{nt})'$ is a t-th row of the $(T \times n)$ matrix $Y = [r_1, ..., r_n] = [y_1, ..., y_T]'$ in the model (1.8).

D Construction of the mimicking portfolios

This appendix describes a procedure for constructing portfolios that mimic non-tradable factors that are used in the analysis. Breeden (1979) and Huberman, Kandel and Stambaugh (1987) provide theoretical grounds for replacing non-tradable factors with their mimicking portfolio returns. Following the approach common in the literature, the latter are expressed in terms of base asset returns that describe the asset space (see, e.g., Breeden, Gibbons and Litzenberger, 1989; Adrian, Etula and Tyler, 2014). This involves the time-series regression given by:

$$E_t = a + b' Z_t + \epsilon_t, \quad t = 1, ..., T, \tag{D1}$$

where E_t is an observation for a non-tradable factor at time t and Z_t is a $g \times 1$ vector of real returns on g base assets. Following Adrian et al. (2014), base assets are given by the momentum factor, 10-year US Treasury bond yield and six Fama-French portfolios of equities (size/book-to-market grouping).

A mimicking portfolio ME_t for the non-tradable factor E_t then obtains as follows:

$$ME_t = w' Z_t, \quad w = (w_1, ..., w_g)', \quad w_j = \hat{b}_j / \sum_{j=1}^{g} \hat{b}_j, \quad j = 1, ..., g, \quad t = 1, ..., T, \tag{D2}$$

where $g \times 1$ vector w collects weights and $\hat{b}_j$, $j = 1, ..., g$, are OLS-based estimates of slope coefficients from the regression (D1).

E Combined goodness-of-fit test

CGF test statistic

Testing a Gaussian distributional assumption on the errors relies on an exact, combined goodness-of-fit (CGF) test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013) reproduced below.

To proceed, define Y as a $T \times n$ matrix of dependent variables. Also, denote as X a $T \times k$ matrix with a vector of ones in the first column and q explanatory variables, such that $k = q + 1$. Further, let $Z = I - X(X'X)^{-1}X'$ and B collect regression coefficients in a $k \times n$ matrix.

Given this notation, CGF test is implemented in the context of the following multivariate linear regression model:

$$Y = XB + U, \tag{E1}$$

where $T \times n$ matrix $U = [U_1, ..., U_n] = [\Upsilon_1, ..., \Upsilon_T]'$ assembles disturbances assumed to have the following distribution:

$$\Upsilon_t = QW_t, \quad t = 1, ..., T, \tag{E2}$$

$$W_t \sim_{i.i.d.} \mathcal{N}(0, I_n), \tag{E3}$$

and Q is a $n \times n$ unknown, full-column matrix.

In this setting, the CGF test is defined for a null hypothesis imposing Gaussian values of skewness and kurtosis, as given in E3. Inference proceeds using a simulated p-value to test statistical significance at level α.

The CGF test involves the skewness and kurtosis of Mardia (1970) for the multivariate setting:

$$S = \frac{\sum_{j=1}^{T} \sum_{t=1}^{T} \hat{h}_{jt}^3}{T^2}, \quad K = \frac{\sum_{t=1}^{T} \hat{h}_{tt}^2}{T}, \tag{E4}$$

such that $\hat{h}_{jt}$ is an observation from matrix $\hat{H} = T\hat{U}(\hat{U}'\hat{U})^{-1}\hat{U}'$ with $\hat{U}$ obtained as OLS residuals from E1. Beaulieu, Dufour and Khalaf (2003) establish distributional invariance of statistics in (E4) to unknown parameters. To that end, they show that distributions of S and K coincide respectively with those of $\frac{1}{T^2} \sum_{j=1}^{T} \sum_{t=1}^{T} h_{jt}^3$ and $\frac{1}{T} \sum_{t=1}^{T} h_{tt}^2$, where h_{jt} is an observation from matrix H positioned in row j and column t:

$$H = TZW(W'ZW)^{-1}W'Z, \quad W = \left[W_1, \;\; ... \;\; , W_T\right]'. \tag{E5}$$

Test implementation incorporates the following simulation-based, excess skewness and kurtosis statistics:

$$E_S = |S - \overline{S}|, \quad E_K = |K - \overline{K}| \tag{E6}$$

which are modified versions of S and K. $\overline{S}$ and $\overline{K}$ are respectively the estimates for the expected values of S and K obtained via the simulation. Transformed statistics E_S and

E_K remain pivotal. This allows to obtain exact p-values for these statistics, denoted as $\hat{p}_N(E_S)$ and $\hat{p}_N(E_K)$ respectively, using the Monte Carlo (MC) method (Dwass, 1957; Barnard, 1963; Dufour, 2006) and given the procedure summarized in F.2.1 - F.2.3 below.

The CGF test relies on the following statistic that considers excess skewness and kurtosis measures together:

$$E_{SK} = 1 - min\{\hat{p}_N(E_S), \hat{p}_N(E_K)\} \tag{E7}$$

Procedure reproduced in F.3.1-F.3.7 below allows to compute an exact, MC p-value for the CGF test based on the E_{SK} statistic.

Monte Carlo Method

Here we restate the MC method available in the literature (see Dwass, 1957; Barnard, 1963; Dufour, 2006). Consider the model given by (E1) and (E2). The MC method applies to a test statistic $C(Y,X)$ for which the following pivotal null representation can be obtained:

$$C(Y,X) = \bar{C}(W,X)$$

with its value given the observed X and Y denoted by $C^{(0)}$.

Then the p-value for such a statistic, $\hat{p}_J[C] = p_J[C^{(0)}, C]$, obtains as:

$$p_J[z, C] \equiv \frac{1 + \sum_{j=1}^{J} I_+ \left[C^{(j)} - z\right]}{1 + J} \tag{E8}$$

where

$$I_+ \left[C^{(j)} - z\right] = \begin{cases} 1, & \text{if } \left[C^{(j)} - z\right] \geq 0, \\ 0, & \text{if } \left[C^{(j)} - z\right] < 0. \end{cases} \tag{E9}$$

with $C^{(j)}$ defined as the simulation-based statistic estimated using the j-th draw of $i.i.d.$ realizations from W: $W_{(j)} = \left[W_1^{(j)}, \ \ldots \ , W_n^{(j)}\right]$, $j = 1, \ \ldots \ , \ J$.

Interval $\hat{p}_J[C] \leq \alpha$, $0 < \alpha < 1$, yields the MC exact critical region such that, imposing the null restriction:

$$P[\hat{p}_J[C] \leq \alpha] = \alpha \tag{E10}$$

when $\alpha(1 + J)$ is an integer and C is continuously-distributed.

F Procedure for implementing the CGF test

Given the model defined in (E1)-(E3), implementation of the CGF test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013) involves three steps outlined in the next three sub-sections.

Simulated moments of skewness and kurtosis

F.1.1 Given $Z = I - X(X'X)^{-1}X'$, assemble the following matrix P times, $p = 1, \ \dots \ , \ P$:

$$H_{(p)} = TZ\tilde{W}_{(p)}(\tilde{W}'_{(p)}Z\tilde{W}_{(p)})^{-1}\tilde{W}'_{(p)}Z, \tag{F1}$$

where $\tilde{W}_{(p)}$ is the p-th *i.i.d.* draw from W given by (E3): $\tilde{W}_{(p)} = \left[\tilde{W}_1^{(p)}, \ \dots \ , \tilde{W}_n^{(p)}\right]$.
F.1.2 For each $H_{(p)}$, estimate skewness and kurtosis measures using (E4). This produces P simulation-based estimates for the latter statistics, denoted respectively by $\bar{S}_{(p)}$ and $\bar{K}_{(p)}$, $p = 1, ..., P$.
F.1.3 Take the average of $\bar{S}_{(p)}$ and $\bar{K}_{(p)}$ across draws to obtain the simulation-based expectations for the skewness and kurtosis:

$$\overline{S} = \frac{\sum_{p=1}^{P} \overline{S}_{(p)}}{P}, \quad \overline{K} = \frac{1 \sum_{p=1}^{P} \overline{K}_{(p)}}{P}, \quad p = 1, ..., P. \tag{F2}$$

Individual tests

F.2.1 Using observed data, estimate excess skewness and kurtosis statistics given by (E6) denoting the resulting values as $E^{(0)} = [E_S^{(0)}, E_K^{(0)}]'$. This relies on the expectations of skewness and kurtosis simulated in the first step as described in F.1.1 - F.1.3.
F.2.2 Generate simulated data making L *i.i.d.* draws from W. For each draw, use the simulated data to compute the associated L simulation-based statistics for excess skewness and kurtosis, $E_{(i)} = [E_S^{(i)}, E_K^{(i)}]'$, $i = 1, \ \dots \ , \ L$. These are produced using the simulated expectations $\bar{S}$ and $\bar{K}$ obtained in F.1.1 - F.1.3.
F.2.3 Estimate exact p-values for statistics in (F2), $\hat{p}_L[S]$ and $\hat{p}_L[K]$, using MC formula given by (E8). The individual test of excess skewness is significant at level α if $\hat{p}_L[S] \leq \alpha$. Test of excess kurtosis follows a similar rule. Both tests are size-correct under the null hypothesis when E is continuously-distributed, that is

$$P[\hat{p}_L[S] \leq \alpha] = P[\hat{p}_L[K] \leq \alpha] = \alpha \tag{F3}$$

given the exchangeability of $E_{(i)}$, $i = 1, \ \dots \ , \ L$.

Combined test

F.3.1 Produce simulated expectations of skewness and kurtosis as in F.1.1 - F.1.3. Use these to compute the excess skewness and kurtosis statistics based on the sample of collected observations, $E^{(0)} = [E_S^{(0)}, E_K^{(0)}]'$, and simulated data as in F.2.1. This generates L simulation-based statistics.
F.3.2 Apply the MC formula in (E8) to generate two separate p-value functions, $p_L[z, C]$ for $C = E_S, E_K$, that depend on L simulated statistics from step F.3.1.
F.3.3 Simulate new data by making L_1 *i.i.d.* draws from W such that $\alpha(L_1 + 1)$ is maintained as an integer.

F.3.4 Use the L_1 realizations of data from the previous step and the simulated moments obtained in F.3.1 to produce the following simulation-based statistics: $E^{(m)} = [E_S^{(m)}, E_K^{(m)}]'$, $m = 1, \ldots, L_1$. That is, for each draw m, $E_S^{(m)}$ and $E_K^{(m)}$ are computed using the new simulation-based data.

F.3.5 Consider again the two p-value functions constructed for E_S and E_K in step F.3.2. Using these functions, compute p-values for the observed and L_1 simulation-based statistics. Denote these respectively as $\hat{p}_L^{(0)}(C) = p_L(C^{(0)}; C)$ and $\hat{p}_L^{(m)}(C) = p_L(C^{(m)}; C)$, $m = 1, \ldots, L_1$ with $C = E_S, E_K$.

F.3.6 Estimate the combined test statistic using p-values from F.3.5 as follows:

$$E_{SK}^{(q)} = 1 - min\{\hat{p}_L(E_S^{(q)}), \hat{p}_L(E_K^{(q)})\}, \quad q = 0, 1, 2 \ldots, L_1. \tag{F4}$$

F.3.7 Given the values $E_{SK}^{(q)}$, $q = 0, 1, 2 \ldots, L_1$ from (F4), the p-value for the combined CGF test is $\hat{p}_{L_1}[E_{SK}] \equiv p_{L_1}[E_{SK}^{(0)}, E_{SK}]$ computed as in (E8). Beaulieu, Dufour and Khalaf (2003) show that the CGF test maintains size control at level α.

Chapter Two

Zero-beta inference on Catastrophe bond mutual funds: identification-robust evidence with non-tradable factors

2.1 Introduction

It is often claimed that Catastrophe bond mutual funds [**CBMFs**] display low sensitivity to the developments in financial markets (LGT Capital Partners, 2015). As such, CBMFs could be viewed as zero-beta investments. These funds mainly invest in Catastrophe bonds covering different perils (e.g., hurricanes, earthquakes) and geographies. Designed to pay coupons and principal if no triggering catastrophe sets off default, Catastrophe bonds aim to eliminate exposure to systematic market risk.[1] Hence, CBMFs may indeed achieve the zero-beta neutrality offering valuable diversification benefits to investors. However, considerable exposure to systematic risk could arise for these mutual funds through the structural weaknesses of Catastrophe bonds. These may include a poor quality of the underlying collateral assets or a counterparty risk. For instance, several Catastrophe bonds defaulted during the 2007-08 financial crisis due to a rapid deterioration in the value of their collateral assets. The latter was compounded by the collapse of the Lehman Brothers, which served as an interest rate swap counterparty for the failed Catastrophe bonds. In the setting with non-tradable factors, this paper offers a formal analysis of whether CBMFs perform as zero-beta assets with respect to financial markets.

The market for Catastrophe bonds has grown considerably since its launch in mid-90s reaching US $30 billion in size and supplying roughly 30% of alternative capital for global property catastrophe reinsurance in 2017 [Artemis (2017), Aon Benfield (2017a)]. With nearly 60% market share, CBMFs have been the largest capacity provider for Catastrophe bonds and attracted a large portion of personal savings [Aon Benfield (2017b)]. Given strong investor demand for CBMFs and their relevance for the reinsurance market, formal analysis of their zero-beta performance could help facilitate prudent investment decisions, avoid instability in financial and reinsurance markets and prevent negative social outcomes that may arise due to unrealistic performance expectations.

Despite their growing importance, few existing studies have examined whether CBMFs are zero-beta neutral. To that end, Cummins and Weiss (2009) use panel data on CBMFs before mid-2008 and estimate a pooled regression with stock and corporate bond benchmarks. Their empirical approach relies on assessing estimated factor loadings, which are

[1] Appendix A contains more information about Catastrophe bonds.

found to be positive and statistically significant. However, small beta estimates suggest that the performance of CBMFs was not far from that of a zero-beta asset before the mid-2008. In the setting with only tradable factors, Chapter 1 of this Thesis provides identification-robust evidence against the zero-beta neutrality of CBMFs between November 2004 and December 2015. The empirical strategy in Chapter 1 consists of assessing whether factors are priced (**beta pricing**) and have jointly significant betas. Reported results indicate risk premiums and non-trivial betas on coskewness, funding liquidity and benchmarks for stock and commercial mortgage-backed securities (CMBS) markets. Related works on the dynamics with financial markets center on Catastrophe bonds and indices (see, e.g., Gürtler, Hibbeln and Winkelvos, 2014; Gomez and Carcamo, 2014; Carayannopoulos and Perez, 2015; Braun, 2015). These studies focus on factor loadings or correlations and do not incorporate information about factor risk premiums into the analysis. Their findings overall suggest that Catastrophe-linked securities tend to underperform as zero-beta assets.

Relative to existing literature, the contribution of this paper is threefold. First, while similar to Chapter 1 of this Thesis in terms of its empirical methodology that considers factor risk premiums and betas, this study differs by extending the zero-beta analysis to a setting with both tradable and non-tradable factors. In particular, Chapter 1 proceeds by restricting all factors to be tradable and for this purpose substituting non-tradable factors with their mimicking portfolios. Regressing non-tradable factors on benchmark asset returns considered to span all assets is a common way to obtain such portfolios (see, e.g., Breeden, 1979; Huberman, Kandel and Stambaugh, 1987; Adrian, Etula and Tyler, 2014). With only tradable factors considered in Chapter 1, inference on risk premiums proceeds using the confidence set estimated for the zero-beta rate.[2] However, it has been argued that replacing non-tradable factors with their mimicking portfolios could undermine beta pricing inference when the relation of these factors with the asset returns is weak (Kleibergen and Zhan, 2018). In particular, regression on base assets amplifies correlations and betas of asset returns with the resulting mimicking portfolios. In effect, projection noise incorporated into mimicking portfolios may lead to distorted empirical estimates that fail to accurately capture pricing information contained in non-tradable factors. Consequently, spurious inference on risk premiums could result. Further, validity of the Gibbons, Ross and Shanken (1989)-type test for inference on cross-sectional coefficients may also be undermined when mimicking portfolios are used. The latter may be biased if projection-based coefficients are estimated with pricing errors (Kleibergen and Zhan, 2018). Given the above, this study introduces non-tradable factors directly to augment a model with a tradable factor.

[2] Zero-beta rate is an expected interest rate on the portfolio with the smallest variance among portfolios that have a zero correlation with any risk factor (Campbell, Lo and MacKinlay, 1997, Chapter 6).

Second, this study constructs identification-robust confidence sets for risk prices and the zero-beta rate and applies them for the beta pricing inference on tradable and non-tradable factors. These sets are assembled using the method of Beaulieu, Dufour and Khalaf (2018) which remains robust regardless of whether the identification of the zero-beta rate and risk prices is weak. In particular, when factor loadings on a tradable factor are jointly close to one and those on non-tradable factors are jointly near zero, this impairs parameter identification. At the extreme, if tradable betas are exactly one and non-tradable betas are at zero, there is a complete failure to recover the zero-beta rate and risk prices. Conventional econometric methods, however, fail to detect and signal this identification problem when it occurs and could be highly misleading for inference. The method of Beaulieu, Dufour and Khalaf (2018) remains robust in the presence of identification problems and provides a warning when the latter arises. This allows to avoid spurious beta pricing inference when identification is weak. For an in-depth zero-beta analysis, beta pricing results are augmented with evidence on the joint statistical significance of factor betas. It is relevant to assess risk premiums in addition to betas. In line with the asset pricing theory, expected asset returns will incorporate no compensation for risk factors if their risk premiums and/or betas, which measure risk exposure, are zero. When risk premiums and/or betas are zero on all factors, an asset is said to be zero-beta neutral. Hence, it is necessary to consider both betas and risk premiums for a reliable zero-beta inference.

Third, the zero-beta analysis of CBMFs incorporates coskewness, funding liquidity and marketwide liquidity benchmarks as non-tradable factors. In particular, estimation proceeds in the context of a Quadratic Capital Asset Pricing Model (QCAPM) Kraus and Litzenberger (1976); Barone-Adesi (1985); Barone-Adesi, Gagliardini and Urga (2004, see, e.g.,). The latter is an extension of a single-factor Capital Asset Pricing Model (CAPM) without the riskless asset introduced by Black (1972) (BCAPM). Apart from the market return, QCAPM also incorporates its square as a second factor. In particular, squared market return is introduced into the model directly as a non-traded factor. Theoretical and empirical results of Barone-Adesi (1985) and Barone-Adesi, Gagliardini and Urga (2004) suggest that squared market return could be used to capture the coskewness risk. Kraus and Litzenberger (1976) theorized that positive market coskewness may be a desirable portfolio property for investors and linked expected asset returns to coskewness beta in their Three Moment Capital Asset Pricing Model. Further, given the underlying catastrophe risk, modeling the dynamics of CBMFs with financial benchmarks as linear may be too restrictive. QCAPM accounts for nonlinearity and may be better suited for analyzing CBMFs. Given the interest in a relation of CBMFs with financial markets, QCAPM is estimated separately for stock, corporate bond, government bond and CMBS market returns and their respective squares.

The literature provides evidence on the relevance of liquidity risk for various assets (see, e.g., Amihud and Mendelson, 1986; Amihud, 2002; Pástor and Stambaugh, 2003). Imposing tradability on the liquidity factor in Chapter 1, we document that liquidity risk may account in part for CBMFs underperforming as zero-beta assets. Relaxing the tradability restriction, this paper extends the analysis in the first Chapter and considers BCAPM model augmented with the non-traded liquidity factor of Pástor and Stambaugh (2003).

There are studies documenting the significance of the funding liquidity factor across assets (see, for example, Fontaine and Garcia, 2012; Fontaine, Garcia and Gungor, 2016; Hu, Pan and Wang, 2013). Restricting the funding liquidity factor to be tradable, Chapter 1 attests to its relevance for the zero-beta performance of CBMFs. This study extends the analysis in the previous Chapter further exploring the role of funding risk for CBMFs without imposing the tradability restriction on this factor. In particular, a model with the BCAPM benchmark along with a differenced funding liquidity factor of Fontaine and Garcia (2012) is estimated.

In terms of empirical findings, despite prevalence of impaired identification, robust confidence sets are informative for inference in many cases and overall suggest that CBMFs were not zero-beta neutral. In particular, full-sample analysis provides evidence of risk premium on coskewness risk across all markets. For stock, corporate bond and CMBS benchmarks, this is also the case after the 2007-09 US recession. There are significant coskewness betas on the stock benchmark pre-recession. Overall, it appears that CBMFs may be sensitive to the developments in financial markets through the coskewness risk, which is broadly in line with findings in Chapter 1.

In addition, the analysis in this study reveals that funding risk is priced both during the economic upturn and over the full sample. For the marketwide liquidity risk, this occurs during the recovery period. The overall indication is that funding and marketwide liquidity risks may be amplifying the relation of CBMFs vis-a-vis financial markets.

The impact of the traditional market beta risk also appears to be pronounced. In particular, QCAPM with stock, corporate bond and CMBS benchmarks have significant market betas in full sample and post-recession. The same holds for both models with liquidity factors. QCAPM market betas are also significant for stocks before the downturn and for the government bond benchmark in the midst of the recession. Altogether, this suggests that CBMFs may have been exposed to a considerable degree of the systematic risk across markets.

Relative to Chapter 1, the fit of all models improves once the tradability restriction is relaxed. Specifically, in the setting with both tradable and non-tradable factors, QCAPM is no longer rejected for any market and period as was the case in Chapter 1 post-crisis and over the full sample. For a liquidity model with the FG factor, the result is the same.

The fit of the CAPM model augmented with the non-tradable PS liquidity factor also improves post-crisis relative to its counterpart in Chapter 1 with only tradable factors. For those periods in which models were rejected in Chapter 1, relaxing the tradability restriction not only improves the model fit, but also yields robust confidence sets that, albeit weakly-identified, are informative for inference on beta pricing.

Sections below are arranged as follows. The model and the empirical strategy are described next. Section 2.3 outlines the methodological approach. Details about the data can be found in Section 2.4. Section 2.5 summarizes empirical evidence. Final section concludes.

2.2 The Model and the Empirical Strategy

Empirical strategy involves testing the joint statistical significance of factor betas from the unrestricted model to assess the overall exposure to systematic risk. This is further augmented with inference on risk premiums and the zero-beta rate to inform on the relevance of risk factors for investors. The latter proceeds using a restriction on parameters.

In particular, consider n asset portfolios indexed by $i = 1, ..., n$ over T periods such that $t = 1, ..., T$. Let r_{it} and ϵ_{it} denote respectively a real return and a disturbance for a portfolio i at time t. Also, denote by $R_t = (R_{1t}, R_{ft})'$ a $q \times 1$ vector of observations on a single tradable factor R_{1t}, for instance a market benchmark, and f non-tradable factors, R_{ft}, with $q = f + 1$. Further, define as $b_i = (b_{1i}, b_{fi})'$ a $q \times 1$ vector of factor loadings where b_{1i} denotes a slope coefficient on a tradable factor and $b_{fi} = (b_{2i}, ..., b_{qi})'$ collects f sensitivities on non-tradable factors.

Given the above, the unrestricted multivariate linear regression (MLR) model is given by (see Shanken, 1992; Beaulieu, Dufour and Khalaf, 2015):

$$r_{it} = a_i + b_{1i}R_{1t} + b'_{fi}R_{ft} + \epsilon_{it}, \qquad i = 1, \ldots, n, \qquad t = 1, \ldots, T. \tag{2.1}$$

In this setting, the empirical strategy tests a joint statistical significance of cross-sectional betas on each factor. That is,

$$H_0^{(1)} : \ b_{ji} = 0, \quad j \in \{1, \ \ldots \ , \ q\}, \quad i = 1, \ \ldots \ , \ n, \tag{2.2}$$

is the joint null hypothesis of interest.

In the setting without a riskless asset, there exist a multifactor zero-beta model [**ZBM**], which is an extension of the single-factor BCAPM (see, e.g., Black, 1972; Shanken, 1992; Beaulieu, Dufour and Khalaf, 2015; Campbell, Lo and MacKinlay, 1997, Chapter 6). Formally, ZBM takes the form:

$$r_{it} - \gamma_0 = b_{1i}(R_{1t} - \gamma_0) + b'_{fi}(R_{ft} - \gamma_f) + \epsilon_{it}, \quad i = 1, \ \ldots \ , \ n, \qquad t = 1, \ldots, T, \tag{2.3}$$

where $f \times 1$ vector γ_f collects risk prices on non-tradable factors. This relation can be further rearranged as follows:

$$r_{it} = \big[(1-b_{1i})\gamma_0 - b'_{fi}\gamma_f\big] + b_{1i}R_{1t} + b'_{fi}R_{ft} + \epsilon_{it}, \quad i = 1, \ldots, n, \qquad t = 1, \ldots, T, \tag{2.4}$$

thus constricting the intercept in (2.1) so that:

$$H_0^{(2)}(\gamma_0, \gamma_f): \; a_i = (1-b_{1i})\gamma_0 - b'_{fi}\gamma_f, \quad i = 1, \ldots, n, \quad \textit{for some unknown } \; \gamma_0, \gamma_f, \tag{2.5}$$

where the expression on the right-hand side is non-linear.

Beta pricing involves constructing confidence sets for the elements of $q \times 1$ vector $\lambda = (\gamma_0, \gamma'_f)'$ as outlined in the next section. These sets are applied for inference given a traditional cross-sectional interpretation (see, e.g., Campbell, Lo and MacKinlay, 1997; Shanken and Zhou, 2007, Chapter 6) based on the following transformation of (2.3)

$$\bar{r}_i = \gamma_0 + b_{1i}(\bar{R}_1 - \gamma_0) + b'_{fi}(\bar{R}_f - \gamma_f) + \bar{\epsilon}_i \quad i = 1, \ldots, n, \tag{2.6}$$

where barred variables indicate time series averages. In the above expression, coefficients on betas signal when a factor is priced: this occurs for a tradable factor when $\bar{R}_1 - \gamma_0 \neq 0$ and for any non-tradable factor when its respective element in $\bar{R}_f - \gamma_f$ differs from zero. Given this, the confidence sets on parameters in λ are applied for the beta pricing inference using the exclusion rule. The latter is satisfied for a given factor when its mean value falls outside of the confidence set on a corresponding element in λ indicating that the factor is priced. For a tradable factor, its mean is assessed against the confidence set for γ_0. For any non-tradable factor, its average is evaluated with respect to a respective component in γ_f.

To restate (2.1), (2.2) and (2.5) more generally, let $T \times n$ matrix Y collect real returns r_{it} for n portfolios over T periods, and assemble all disturbances ϵ_{it} into a $T \times n$ matrix U. Further, gather observations on q factors and a $T \times 1$ vector of ones, ι_T, into a $T \times k$ full-column matrix $X = [\iota_T, R_1, R_f]$, where R_1 and R_f are respectively $T \times 1$ and $T \times f$ and contain observations on a single tradable and f non-tradable factors. Also, collect all coefficients into a $k \times n$ matrix B given below

$$B = \begin{bmatrix} a' \\ b \end{bmatrix} \quad b = \begin{bmatrix} b'_1 \\ b_f \end{bmatrix} = \begin{bmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_q \end{bmatrix}, \tag{2.7}$$

where a and b_1 are $n \times 1$ vectors of respectively intercepts and loadings on the tradable factor, while b_f denotes a $f \times n$ matrix of sensitivities on non-tradable factors. Given the above, a more general model is given by:

$$Y = XB + U \tag{2.8}$$

with the hypotheses (2.2) and (2.5) restated as:

$$H_0^{(1)}: c_k[j]'B = 0, \quad j \in \{2, \ldots, k\}, \tag{2.9}$$

and

$$H_0^{(2)}(\lambda) : (1, \lambda)' P = 0, \quad \textit{for some unknown} \;\; \lambda = (\gamma_0, \gamma_f')', \quad P = \begin{bmatrix} a' \\ (b_1 - \iota_n)' \\ b_f \end{bmatrix} \tag{2.10}$$

where $(k \times 1)$ vector $c_k[j]$ contains a single non-zero value equal to one in the position j and is used to retrieve loadings on a factor j from B.

OLS estimators associated with (2.8) are defined as follows:

$$\hat{B} = \begin{bmatrix} \hat{a}' \\ \hat{b} \end{bmatrix} = (X'X)^{-1}(X'Y), \quad \hat{S} = \hat{U}'\hat{U}, \quad \hat{\Sigma} = T^{-1}(\hat{U}'\hat{U}), \tag{2.11}$$

$$\hat{U} = Y - X\hat{B}, \quad \hat{P} = \begin{bmatrix} \hat{a}' \\ (\hat{b}_1 - \iota_n)' \\ \hat{b}_f \end{bmatrix}$$

The six estimated models include QCAPM with either stock, corporate bond, government bond or CMBS market return and its respective square. In addition, BCAPM augmented with either the differenced funding liquidity factor of Fontaine and Garcia (2012) or the non-tradable marketwide liquidity factor of Pástor and Stambaugh (2003) is also considered.

2.3 Methodological Approach

2.3.1 Significance of factor loadings

Testing a joint statistical significance of factor loadings, as per (2.9), relies on the following exact, multivariate Hotelling statistic (Hotelling, 1947):

$$\Psi_j = \frac{e_k[j]'\hat{B}\hat{S}^{-1}\hat{B}'e_k[j]}{e_k[j]'(X'X)^{-1}e_k[j]}, \quad j \in \{1, \; \ldots \; , \; q\}. \tag{2.12}$$

with a Fisher distribution under *i.i.d.* jointly Gaussian errors:

$$\Psi_j \frac{d}{n} \sim \mathcal{F}\left(n, d\right), \quad d = T - k - n + 1, \quad \textit{under } H_1 \tag{2.13}$$

The decision rule for rejecting (2.9) is defined as:

$$\Upsilon_j > \mathcal{F}_{n,d,\alpha}, \quad d = T - k - n + 1, \tag{2.14}$$

where $\mathcal{F}_{n,d,\alpha}$ is the critical point extracted from the $\mathcal{F}$-distribution at level α and $\Upsilon_j = \Psi_j \frac{d}{n}$.

2.3.2 Identification-robust confidence sets

Building exact, identification robust confidence sets for γ_0 and γ_f relies on the method of Beaulieu et al. (2018) that requires inverting the Hotelling test defined for (2.10). This builds on the following statistic:

$$\Psi(\lambda) = \frac{(1,\lambda)'\hat{P}\hat{S}^{-1}\hat{P}'(1,\lambda)}{(1,\lambda)'(X'X)^{-1}(1,\lambda)} \tag{2.15}$$

Inversion procedure calls for fixing λ to a value $\dot{\lambda}$ from an admissible set Γ, successively considering all set values. For any value $\dot{\lambda}$ and *i.i.d.* jointly Gaussian errors, the distribution of this statistic becomes Fisher

$$\Psi\left(\dot{\lambda}\right)\frac{d}{n} \sim F(n,d), \quad d = T-k-n+1, \quad under\ H_0^{(2)}(\dot{\lambda}), \tag{2.16}$$

For each value $\dot{\lambda}$ from Γ, the null hypothesis (2.9) is tested sequentially at a level α using the following rule:

$$\Psi\left(\dot{\lambda}\right)\frac{d}{n} < F_{n,d,\alpha}, \quad d = T-k-n+1. \tag{2.17}$$

Keeping only those values of λ for which inequality (2.17) is satisfied produces the joint region for γ_0 and components of γ_f with the confidence level at least $(1-\alpha)$. Individual confidence sets result from projecting the region onto the parameter axes. The entire procedure is implemented analytically using the solution proposed by Beaulieu, Dufour and Khalaf (2018). This solution relies on the quadrics-based method of Dufour and Taamouti (2005) and is reproduced in the Appendix B.

Resulting confidence sets are exact, simultaneous and identification-robust in the following sense. For any sample size, the inclusion probability covers all parameters and is controlled at a significance level α regardless of an identification strength. In other words, confidence sets will concurrently include the true values of respective parameters with the joint probability $(1-\alpha)$ for any sample size and a degree of identification.

Identification strength and a goodness-of-fit determine the shape of identification-robust confidence sets. In total, there are four possibilities: (1) closed interval; (2) union of two sets; (3) real line; (4) void set. In the first two cases, there is respectively a complete or partial identification. The last two options arise respectively if the parameter recovery fails completely and in the case of a rejected model. The latter occurs if there are no parameter values satisfying the model that the data would not reject.

2.3.3 Conventional confidence sets

Besides identification-robust confidence sets estimated for the components in λ, this paper also provides their conventional counterparts for comparison. To assemble the latter, the maximum likelihood (ML) estimators and their asymptotic variances are used. These could be obtained using the analytical formulas of Beaulieu, Dufour and Khalaf (2018) reproduced in the Appendix C. Following the usual approach, a conventional confidence set could be constructed by adding (and subtracting) the ML parameter estimate to the product of its asymptotic standard error and a cut-off point. This procedure, by design, always produces closed intervals regardless of the parameter identification strength and the goodness-of-fit. As a result, these conventional intervals are misleading for inference when there is an insufficient degree of an identification or a lack of fit. In particular, when the tradable beta is exactly at one and the non-tradable betas are equal to zero jointly across equations, parameters are unidentified. The parameter solution in this case should be the entire real line. In contrast, conventional confidence sets remain closed even when a parameter identification breaks down entirely. The latter are also misleading in a less extreme case when a partial identification is possible. With conventional intervals, there is no control over the probability of a parameter inclusion, which could be quite negligible under the weak or failed identification. This makes conventional methods unreliable for the inference when the identification is undermined.

Unlike their conventional analogs, simultaneous, identification-robust confidence sets remain valid regardless of the degree of identification. In particular, parameter inclusion is guaranteed with a probability of $(1 - \alpha)$ over all confidence sets irrespective of the sample size and whether the parameter recovery is feasible.

Empirical estimates reported in Section 2.5 reveal a marked difference between the robust and conventional sets in cases when identification is weak and underscore the advantage of using the former.

2.4 Data

The overall study period for the analysis in this paper extends between 11/2004 - 12/2015. Empirical results are provided for the full sample. Sub-sample analysis is performed for 3 sub-periods before, during and after the 2007-09 US recession: 11/2004 - 11/2007, 12/2007 - 06/2009, 07/2009 - 12/2015.[3] All data is monthly.

Prices for seven CBMFs come from Bloomberg. To have the same currency for all funds, prices in Euros or Franks are converted into US dollars using exchange rates (DEXUSEU and DEXSZUS) from the Federal Reserve Economic Data (FRED) available online. After that, US-dollar prices are used to compute real returns on CBMFs as follows $[ln(f_t) - ln(f_{t-1})] - i_t$ with f_t and f_{t-1} indicating funds' prices at time t and $t-1$ respectively and i_t denoting time-t inflation rate. The latter is based on the seasonally-adjusted US CPI index less food and energy (CPILFESL) downloaded from FRED. Time series of real returns on CBMFs are displayed in Figures 2.1 and 2.2.

[3] This follows the timeline from the National Bureau of Economic Research.

For the stock market, the return for the portfolio comprising of stocks from NYSE, AMEX and Nasdaq (VWRETD, value-weighted) is used as a benchmark. This data is downloaded from Center for Research in Security Prices (CRSP).

Corporate bond market is represented using time series on the Bank of America Merrill Lynch US High Yield Total Return Index (BAMLHYH0A0HYM2TRIV) retrieved from FRED. US Treasury and CMBS benchmarks are constructed using Bloomberg data on respectively Bloomberg Barclays US treasury total return index (LUATTRUU) and Bloomberg Barclays CMBS Investment grade Total return index (LC09TRUU). For corporates, treasury and CMBS benchmarks, returns are estimated as $[ln(M_t) - ln(M_{t-1})]$ with M_t and M_{t-1} indicating index observations at time t and $t-1$ respectively.

For each of the four markets, we use as factors spreads of the respective market return and its square over the CPI-based inflation rate.

Data on the FG and PS factors comes from websites of respectively Jean-Sébastien Fontaine and Lubos Pastor.

2.5 Empirical Results

In this section, we report estimated sample moments for all time-series. Results for testing Gaussian errors are also provided.

Table 2.3 displays the first four sample moments estimated for the risk factors and real returns on CBMFs. Mean returns for most CBMFs are positive over the full sample and during the tranquil periods and are similar in terms of variance. The latter goes up during the recession for the majority of funds. Throughout the downturn, almost all CBMF display negative mean returns. There is some variability in terms of excess skewness and kurtosis across funds. These moments also vary considerably over time.

Mean market returns are positive across all benchmarks over the entire study period and during normal economic conditions. During the recession, mean returns turn negative for all markets but the Treasuries. Among the four markets, stock return varies the most. For all benchmarks, market returns become more volatile during the recession. All market benchmarks display excess skewness and kurtosis. The latter are most pronounced for the corporates and CMBS over the full sample.

Squared market returns for corporates and CMBS have negative means during tranquil periods and over the full sample, but become positive during the times of financial stress. Treasuries display negative mean squared returns throughout. Except for the initial tranquil sub-period, average mean return is always positive for the stock benchmark. Relative to market returns, their squared counterparts are less volatile across all benchmarks. Compared to their levels, squared returns have a higher degree of kurtosis during and after the recession and over the full sample. For all squared benchmarks, excess skewness switches from negative to positive in the first two sub-periods and remains above zero during the upturn and over the entire study period.

FG and PS factors are both positive on average in all periods except during the recession. Both also become more volatile during the financial turmoil. Relative to any other risk benchmark, FG factor varies more in all periods. Both liquidity factors have a moderate degree of excess skewness and kurtosis.

Table 2.4 reports estimated correlations for the risk benchmarks and real returns on CMBFs. Correlations estimated for CBMFs vary considerably among the fund pairs in all periods. Except for one pair of funds with a negative dynamics during the recession, all CBMFs are always positively correlated with each other.

Market returns for stock, corporates and CMBS are all positively correlated with returns on CBMFs in all periods. These correlations become more pronounced during the recession and remain elevated for many funds during the upturn.

The correlations with squared returns for stocks and corporates are all negative over the full sample. This is driven by the highly negative relationship with funds' returns during the recession. The latter turns positive for all funds during the recovery period. Relative to squared returns on treasuries, correlations are initially negative but mostly exceed zero during the recession. Over the full sample and post-recession, the direction of the relationship with treasuries varies across funds. Overall, the relationship with squared returns on treasuries tend to be less pronounced as compared to stocks and corporates. Except for the initial period, squared returns on CMBS benchmark are mostly positively related to CMBFs.

The dynamics with the PS factor varies considerably over time. The latter correlates mostly negatively with CBMFs until the start of the recession when the direction of the relationship begins to reverse for some funds and subsequently turns positive for all CBMFs during the recovery period. In absolute terms, correlations with the PS factor become more pronounced during the recession. Except for the post-recession period, the relationship with the FG factor is mostly negative and becomes stronger in absolute terms during the downturn.

We also provide a summary of p-values for testing $i.i.d.$ Gaussian errors. Estimates are produced using the Combined Goodness-of-Fit (CGF) test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013) defined for the joint null hypothesis of a Gaussian skewness and kurtosis. The implementation procedure for the CGF test is restated in the Appendix D.

Test results are available in the Table 2.2. Given small estimates of p-values, normality is rejected for all models and periods. Despite this, Gaussian-based results allow for a reliable zero-beta inference on CBMFs. Simulation results of Beaulieu, Dufour and Khalaf (2018) offer supporting evidence for this. According to their findings, identification-robust approach remains statistically precise under the assumption of Gaussian errors even if the true distributional setting is Student-t or GARCH. When the Fisher-based critical value is used, the underlying Hotelling test is shown to be statistically reliable irrespective of the true tail thickness and the degree of skewness in the errors. This lends support for using the Gaussian-based results for inference on the zero-beta performance of CBMFs. Further, Chapter 3 provides formal goodness-of-fit evidence based on Student-t errors.

2.5.1 Regression results

Here we discuss results of the regression analysis that are displayed in Tables 2.5-2.8. Estimates consist of p-values for the beta significance test, factor mean values and confidence sets on the zero-beta rate and risk prices.

Estimates for the QCAPM with stock and corporate bond benchmarks are respectively displayed in Panels A and B of the Table 2.5, while those for Treasuries and CMBS are available respectively in Panels A and B of the Table 2.6. As evidenced by the results, prevalence of weak identification across models highlights the advantage of robust confidence sets over their conventional analogs. When identification weakens, the former either take the form of a union of two sets or extend to the entire real line. For their conventional analogs, however, a resulting set estimate is a closed interval even when identification fails. This undermines the validity of inference based on such traditional set estimates. Given the robust confidence statements, beta pricing inference can proceed in many cases despite identification problems. Notably, there is evidence of priced coskewness risk for stock, corporate bond and CMBS markets during the recovery period and over the full sample. The same result obtains from the QCAPM with the government bond benchmark over the full study period. This is a feature that we could not quantify in Chapter 1 due to the lack of fit for QCAPM post-crisis and over the long-run. Further, the joint significance of coskewness betas with respect to the stock market indicates a considerable exposure to the systematic coskewness risk during the initial tranquil subperiod. Overall, it appears that the sensitivity of CBMFs to the developments in financial markets may have been pronounced due to the coskewness risk.

QCAPM results also reveal heightened sensitivity with respect to the traditional market return across markets. In particular, market betas are jointly significant for stock, corporate bond and CMBS benchmarks over the full sample and post-recession. This also holds for stocks before the downturn and for government bonds during the recovery period. Overall, QCAPM provides robust evidence against CBMFs performing as zero-beta neutral. These findings are broadly congruent with those in Chapter 1 obtained under the tradability restriction.

Relative to results reported in Chapter 1, a notable finding in this study is that QCAPM is not rejected anymore across all periods and markets once the coskenwess factor is introduced as a non-tradable factor. Thus, it appears that relaxing the tradability restriction improves the overall fit of the QCAPM model with respect to all markets. Moreover, using non-tradable factors in the QCAPM instead of their mimicking portfolios not only improves the goodness-of-fit post-crisis and over the full sample, but it also yields identification-robust confidence sets that are informative for beta pricing inference even though some identification issues are present.

Estimates for the liquidity models with either FG or PS factors are available in Tables 2.7 and 2.8 respectively. As with QCAPM, both liquidity models experience considerable identification problems. Nevertheless, identification-robust confidence sets facilitate beta pricing inference in many cases. Notably, funding risk is priced during the upturn period and over the full sample. For the marketwide liquidity risk, this result holds only after the recession as the model with PS factor is rejected over the full sample. Hence, the liquidity model with the FG factor experiences similar improvement in the fit as the QCAPM models once the tradability restriction is relaxed. For the PS-based model, the impact is less pronounced. Taken together, it appears investors in CBMFs placed a premium on the liquidity risk. In terms of beta significance, liquidity betas are non-trivial only for the PS factor over the full sample. Overall, liquidity emerges as another relevant factor that may be amplifying the sensitivity of CBMFs with respect to financial markets. Despite weaker identification, the result on liquidity survives relaxing the tradability restriction.

Both liquidity models provide evidence on the considerable exposure to the systematic risk via the traditional market benchmark. To that end, market betas in both models are jointly significant during and after the recession as well as over the full sample. Taken together, liquidity models suggest that the performance of CBMFs was different from that of a zero-beta asset at least since the beginning of the recession. Liquidity risk appears to contribute in this regard. Chapter 1 reports overall similar findings with tradable liquidity factors. However, relaxing tradability restriction tends to yield a better model fit. It is worth noting that in periods when liquidity models demonstrate an improved fit relative to that in Chapter 1, estimated robust confidence sets facilitate inference on risk prices even though identification becomes harder.

Altogether, empirical evidence suggests that CBMFs tend to fall short of the zero-beta performance. In this respect, liquidity and coskewness may be among the contributing factors.

2.6 Conclusion

The focus of this study is to evaluate whether the performance of CBMFs is zero-beta neutral in the setting with both tradable and non-tradable factors. The paper analyzes the sensitivity of CBMFs vis-a-vis financial markets in two respects. The overall exposure to the systematic risk is examined by testing the joint significance of factor loadings.

In addition, assessing the sensitivity to fluctuations in factor risk further informs on the zero-beta performance. The latter is performed by assessing the loadings on factor betas. This informs on whether investors in CBMFs price factor risks. To that end, identification-robust confidence sets for the factor risk prices are constructed using the method of Beaulieu, Dufour and Khalaf (2018). These results are new to the literature on CBMFs.

In addition, our study fills the literary void on the zero-beta performance of CBMFs by making available results with non-tradable factors. In particular, QCAPM with the squared market return as a non-tradable coskewness factor is estimated individually for several markets. The analysis also covers the BCAPM augmented with a non-tradable liquidity factor. For the latter, either the funding liquidity factor of Fontaine and Garcia (2012) or the marketwide liquidity factor of Pástor and Stambaugh (2003) is considered. Results provide evidence of priced coskewness, funding and marketwide liquidity risks. Further, coskewness and liquidity betas are significantly different from zero in some cases. For QCAPM and both liquidity models, market betas are often significant. There is an overall indication that the performance of CBMFs was not consistent with that of a zero-beta asset. In terms of the parameter recovery, evidence of persistent identification problems underscores the relevance of using the robust inference method.

Relative to Chapter 1, relaxing the tradability restriction for the coskewness and liquidity factors tends to improve the goodness-of-fit for all models. In particular, QCAPM performs well in terms of fit for any market and period. The same result holds for the liquidity model with the FG factor. For the models with an improved fit, the additional benefit of using non-tradable factors directly is that the resulting identification-robust confidence sets, albeit weakly-identified, inform on whether factors are priced.

The inferior model fit observed in the setting with tradable-only factors could be due to mimicking returns failing to capture accurately the pricing information in non-tradable factors (Kleibergen and Zhan, 2018). Relaxing the tradability restriction in Chapter 2 is more consistent with the data as non-tradable factors may be a better proxy (than returns that mimic them) for tradable factors capturing systematic risks.

Alternatively, there is a strand of asset pricing literature which does not require that factors are all necessarily tradable. In particular, Merton (1973) developed a theoretical intertemporal CAPM which in addition to market benchmark also incorporates state variables (not necessarily tradable) that capture investors's desire to offset risks related to changes in future investment opportunities. When deciding what factors to consider for asset valuation, Chen, Roll and Ross (1986) also prescribe choosing factors that could affect expected future cashflows or a discount factor for an asset in addition to state variables describing the investment opportunity set. Following their own prescriptions, the authors choose expected and unexpected inflation and industrial production growth as factors for asset pricing and provide empirical evidence on their relevance. As such, non-tradable factors incorporated directly in Chapter 2 may themselves represent state variables relevant for asset valuation of CBMFs, which may explain the improved model fit that results once tradability is relaxed.

Figures

Figure 2.1: Real returns on CBMFs between 11/2004 − 12/2015 (Panel A)

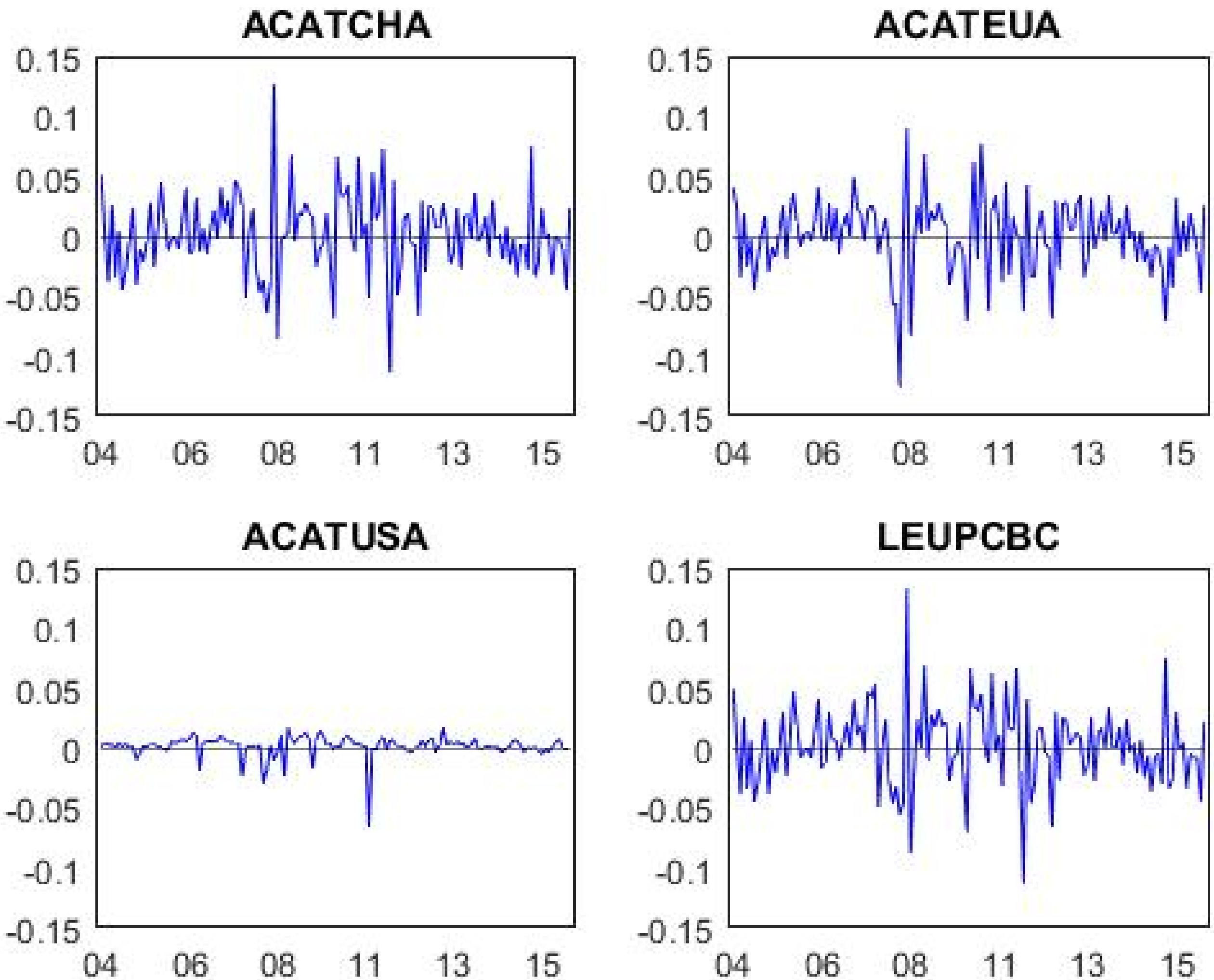
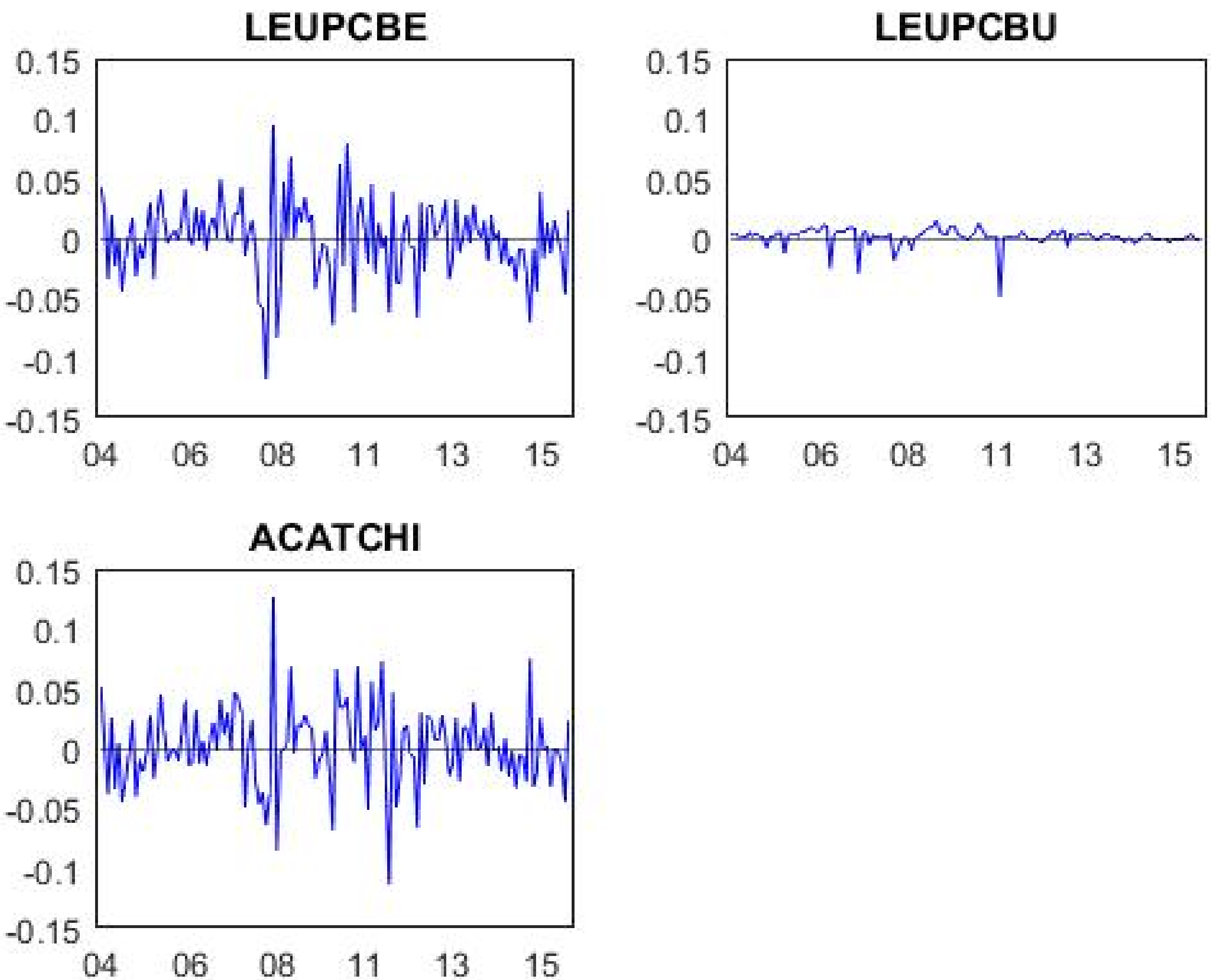


Figure 2.2: Real returns on CBMFs between 11/2004 − 12/2015 (Panel B)



Tables

Table 2.1: List of CBMFs

#	Bloomberg Ticker	Fund Name
1	ACATCHA	Falcon Cat Bond Fund Class A CHF
2	ACATEUA	Falcon Cat Bond Fund Class A EUR
3	ACATUSA	Falcon Cat Bond Fund Class A USD
4	ACATCHI	Falcon Cat Bond Fund Class I CHF
5	LEUPCBC	LGT CH Cat Bond Fund (CHF) A
6	LEUPCBE	LGT CH Cat Bond Fund (EUR) A
7	LEUPCBU	LGT CH Cat Bond Fund (USD) A

Table 2.2: Test of Gaussian errors

#	Model	Period			
		11/2004 - 11/2007	12/2007 - 06/2009	07/2009 - 12/2015	11/2004 - 12/2015
1	QCAPM: stock	0.001	0.001	0.001	0.001
2	QCAPM: corp	0.001	0.001	0.001	0.001
3	QCAPM: govt	0.001	0.001	0.001	0.001
4	QCAPM: CMBS	0.001	0.001	0.001	0.001
5	BCAPM + ΔFG	0.001	0.001	0.001	0.001
6	BCAPM + PS	0.001	0.001	0.001	0.001

Note: Reported estimates are p-values for the Combined Goodness-of-Fit (CGF) test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013). The test is defined for the joint null hypothesis of of a Gaussian skewness and kurtosis.

Table 2.3: Descriptive statistics

#	Variable	11/2004 - 11/2007				12/2007 - 06/2009				07/2009 - 12/2015				11/2004 - 12/2015			
		Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt
1	$R_{acatcha}$	0.002	0.024	0.07	2.36	-0.001	0.049	0.63	3.42	0.002	0.032	-0.42	4.42	0.001	0.033	0.02	4.61
2	$R_{acateua}$	0.005	0.021	-0.13	2.61	-0.004	0.048	-0.59	3.68	-0.002	0.030	-0.21	3.08	0.000	0.031	-0.56	4.77
3	$R_{acateusa}$	0.003	0.005	-1.63	7.55	-0.003	0.012	-0.88	2.71	0.002	0.009	-5.24	39.85	0.001	0.009	-3.91	27.21
4	$R_{leupcbc}$	0.003	0.024	-0.04	2.50	0.000	0.051	0.66	3.28	0.001	0.031	-0.45	4.48	0.002	0.033	0.08	4.88
5	$R_{leupcbe}$	0.005	0.022	-0.21	2.65	-0.004	0.050	-0.32	3.02	-0.003	0.030	-0.16	3.16	-0.001	0.032	-0.39	4.28
6	$R_{leupcbu}$	0.002	0.008	-2.52	9.31	-0.001	0.006	-1.30	4.11	0.001	0.007	-4.73	37.00	0.001	0.007	-3.42	21.46
7	$R_{acatchi}$	0.002	0.024	0.09	2.37	-0.001	0.049	0.62	3.40	0.002	0.032	-0.43	4.46	0.002	0.033	0.03	4.62
8	R_{stock}	0.009	0.025	-0.47	2.29	-0.021	0.072	-0.24	2.63	0.010	0.039	-0.13	3.03	0.005	0.044	-0.79	5.18
9	R_{corp}	0.003	0.013	-1.22	3.91	-0.004	0.064	-0.83	3.97	0.006	0.020	-0.06	3.57	0.004	0.029	-1.70	14.38
10	R_{govt}	0.002	0.010	0.10	2.40	0.003	0.019	0.62	3.44	0.001	0.010	-0.03	2.98	0.002	0.012	0.46	4.70
11	R_{cmbs}	0.001	0.009	-0.07	1.89	-0.009	0.071	-0.58	5.13	0.006	0.013	1.60	8.92	0.002	0.029	-2.01	27.42
12	R^2_{stock}	-0.001	0.001	-0.27	2.22	0.004	0.008	2.64	10.35	0.000	0.002	2.01	7.81	0.000	0.004	5.13	40.78
13	R^2_{corp}	-0.002	0.001	-0.19	2.85	0.003	0.008	2.75	10.55	-0.001	0.001	1.41	5.64	-0.001	0.003	7.28	67.64
14	R^2_{govt}	-0.002	0.001	-0.24	3.11	-0.001	0.001	1.30	4.10	-0.001	0.001	0.77	4.34	-0.001	0.001	0.81	5.45
15	R^2_{cmbs}	-0.002	0.001	-0.18	2.91	0.003	0.011	2.64	9.08	-0.001	0.001	2.89	15.04	-0.001	0.005	7.58	66.52
16	ΔFG	0.007	0.273	1.00	4.63	-0.022	0.533	0.50	2.49	0.004	0.274	-0.77	5.54	0.001	0.323	0.15	4.83
17	PS	0.004	0.058	-0.85	4.80	-0.035	0.097	-0.29	2.50	0.015	0.038	0.25	3.05	0.005	0.058	-1.13	6.15

Note: Sample moments estimated for CBMFs are reported in rows 1-7. R_{stock}, R^2_{stock}, R_{corp}, R^2_{corp}, R_{govt}, R^2_{govt}, R_{cmbs}, R^2_{cmbs} are respectively returns and their squares for stock, corporate bond, government bond and CMBS benchmarks, expressed in excess of inflation. ΔFG is the 1st difference for the funding liquidity factor of Fontaine and Garcia (2012). PS is the liquidity factor of Pástor and Stambaugh (2003).

Table 2.4: Descriptive statistics - correlations

#	Variable	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi
		Before Recession: 11/2004 - 11/2007							**During Recession: 12/2007 - 06/2009**						
1	$R_{acatcha}$	1							1						
2	$R_{acateua}$	0.9533	1						0.8833	1					
3	$R_{acateusa}$	0.2837	0.3182	1					0.1274	0.2501	1				
4	$R_{leupcbc}$	0.9850	0.9402	0.1642	1				0.9825	0.8570	-0.0229	1			
5	$R_{leupcbe}$	0.9280	0.9790	0.2731	0.9350	1			0.8695	0.9764	0.1013	0.8819	1		
6	$R_{leupcbu}$	0.1278	0.1858	0.6161	0.0986	0.3042	1		0.3326	0.4790	0.4564	0.3289	0.5179	1	
7	$R_{acatchi}$	0.9985	0.9493	0.2847	0.9843	0.9242	0.1276	1	0.9999	0.8821	0.1247	0.9831	0.8692	0.3339	1
8	R_{stock}	0.0608	0.1809	0.1016	0.0772	0.2405	0.3253	0.0603	0.3686	0.5915	0.2551	0.3935	0.6275	0.5832	0.3658
9	R_{corp}	0.1251	0.2198	0.2599	0.1361	0.2600	0.3694	0.1263	0.4073	0.5743	0.3985	0.3896	0.5652	0.6315	0.4054
10	R_{govt}	0.1323	0.0710	0.3249	0.0805	0.0060	-0.0837	0.1467	0.3526	0.3553	-0.2112	0.3692	0.3800	-0.0273	0.3510
11	R_{cmbs}	0.1534	0.1260	0.3190	0.1324	0.1123	0.1426	0.1648	0.5840	0.5332	0.0050	0.6186	0.5730	0.4345	0.5824
12	R^2_{stock}	0.1466	0.1347	0.0728	0.1185	0.1119	-0.0633	0.1657	-0.3404	-0.5690	-0.2699	-0.3198	-0.5523	-0.5814	-0.3426
13	R^2_{corp}	-0.0563	-0.0399	0.0340	-0.0596	-0.0377	0.0400	-0.0360	-0.2381	-0.4813	-0.2528	-0.2134	-0.4457	-0.4747	-0.2389
14	R^2_{govt}	-0.0385	-0.0503	-0.0168	-0.0423	-0.0639	-0.0721	-0.0201	0.0933	0.1320	-0.0547	0.0703	0.1182	-0.1681	0.0912
15	R^2_{cmbs}	-0.0798	-0.0719	-0.0281	-0.0687	-0.0577	0.0447	-0.0611	0.0720	0.1246	-0.0472	0.0511	0.1164	-0.1688	0.0709
16	ΔFG	-0.2874	-0.2695	-0.0353	-0.2913	-0.2415	0.0620	-0.2817	-0.5770	-0.5329	-0.3358	-0.5387	-0.4915	-0.4183	-0.5735
17	PS	-0.0676	-0.0835	-0.0396	-0.0853	-0.0612	0.0728	-0.0724	-0.1286	0.1414	0.5874	-0.2020	0.0667	0.3032	-0.1319
		After Recession: 07/2009 - 12/2015							**Full Sample: 11/2004 - 12/2015**						
1	$R_{acatcha}$	1							1						
2	$R_{acateua}$	0.6462	1						0.7616	1					
3	$R_{acateusa}$	0.2385	0.2131	1					0.2132	0.2431	1				
4	$R_{leupcbc}$	0.9935	0.6476	0.1685	1				0.9877	0.7566	0.1110	1			
5	$R_{leupcbe}$	0.6251	0.9911	0.1311	0.6402	1			0.7433	0.9844	0.1466	0.7620	1		
6	$R_{leupcbu}$	0.1959	0.2247	0.9074	0.1596	0.1839	1		0.1967	0.2580	0.7224	0.1700	0.2705	1	
7	$R_{acatchi}$	0.9997	0.6473	0.2382	0.9931	0.6262	0.1948	1	0.9996	0.7612	0.2118	0.9876	0.7432	0.1960	1
8	R_{stock}	0.3896	0.5584	0.0281	0.4051	0.5683	0.1081	0.3861	0.3373	0.5167	0.1491	0.3529	0.5388	0.2547	0.3341
9	R_{corp}	0.4893	0.4707	0.1484	0.5064	0.4811	0.1995	0.4861	0.3854	0.4668	0.2614	0.3865	0.4708	0.3022	0.3836
10	R_{govt}	-0.0436	-0.2725	0.0221	-0.0255	-0.2574	0.0990	-0.0398	0.1187	0.0088	-0.0138	0.1314	0.0186	0.0143	0.1228
11	R_{cmbs}	0.3376	0.2352	0.2918	0.3610	0.2470	0.3551	0.3344	0.3947	0.3477	0.1228	0.4262	0.3734	0.2429	0.3942
12	R^2_{stock}	0.0584	0.1825	0.1485	0.0620	0.1890	0.2286	0.0543	-0.1285	-0.2180	-0.1231	-0.1247	-0.2130	-0.1191	-0.1293
13	R^2_{corp}	0.0199	0.1174	0.1858	0.0376	0.1308	0.2801	0.0145	-0.1276	-0.2572	-0.1561	-0.1138	-0.2389	-0.1341	-0.1273
14	R^2_{govt}	-0.0157	-0.1236	0.0734	-0.0051	-0.1219	0.1386	-0.0223	0.0102	-0.0571	-0.0151	0.0047	-0.0630	-0.0138	0.0108
15	R^2_{cmbs}	0.0702	0.0475	0.1582	0.0961	0.0640	0.2277	0.0649	0.0299	0.0448	-0.0727	0.0294	0.0466	-0.0618	0.0303
16	ΔFG	0.0881	-0.0077	0.0283	0.0897	-0.0076	0.0756	0.0902	-0.2041	-0.2370	-0.0910	-0.2008	-0.2214	-0.0293	-0.2015
17	PS	0.1083	0.0507	0.1648	0.1068	0.0573	0.1672	0.1049	-0.0093	0.0592	0.2914	-0.0501	0.0353	0.1686	-0.0132

Note: Rows 1-7 contain results for CBMFs. R_{stock}, R^2_{stock}, R_{corp}, R^2_{corp}, R_{govt}, R^2_{govt}, R_{cmbs}, R^2_{cmbs} are respectively returns and their squares for stock, corporate bond, government bond and CMBS benchmarks, expressed in excess of inflation. ΔFG is the 1st difference for the funding liquidity factor of Fontaine and Garcia (2012). PS is the liquidity factor of Pástor and Stambaugh (2003)

Table 2.5: QCAPM (stocks and corporate bonds)

Period	**RCS**(γ_0)	**CS**(γ_0)	Mkt	**RCS**(γ_1)	**CS**(γ_1)	Mkt^2
Panel A: QCAPM - stocks						
11/2004 - 11/2007	$\mathbb{R}$	{0.0002, 0.0025}*	0.0086	$\mathbb{R}$	{-0.0018, -0.0010}	-0.0012
			(**0.04**)			(**0.04**)
12/2007 - 06/2009	$\mathbb{R}$	{-0.0032, 0.0009}*	-0.0209	$\mathbb{R}$	{0.0033, 0.0141}	0.0040
			(0.09)			(0.24)
07/2009 - 12/2015	$\mathbb{R}$	{-0.0081, 0.0219}	0.0104	$]-\infty, -0.0038] \cup [0.0017, +\infty[$*	{-0.0080, 0.0312}	0.0002
			(**0.00**)			(0.56)
11/2004 - 12/2015	$\mathbb{R}$	{-0.0604, 0.0710}	0.0055	$]-\infty, -0.0032] \cup [0.0047, +\infty[$*	{-1.3422, 1.1148}	0.0004
			(**0.00**)			(0.85)
Panel B: QCAPM - corporate bonds						
11/2004 - 11/2007	$\mathbb{R}$	{-0.0046, 0.0049}	0.0030	$\mathbb{R}$	{-0.0091, 0.0003}	-0.0018
			(0.26)			(0.61)
12/2007 - 06/2009	$\mathbb{R}$	{-0.0052, 0.0002}	-0.0040	$\mathbb{R}$	{0.0032, 0.0185}*	0.0025
			(0.40)			(0.18)
07/2009 - 12/2015	$]-\infty, -0.0053] \cup [-0.0011, +\infty[$	{-0.0048, 0.0197}	0.0060	$]-\infty, -0.0033] \cup [-0.0004, +\infty[$*	{-0.0021, 0.0065}	-0.0010
			(**0.00**)			(0.05)
11/2004 - 12/2015	$\mathbb{R}$	{-0.0751, 0.0635}	0.0037	$]-\infty, -0.0036] \cup [0.0030, +\infty[$*	{-1.0453, 0.8686}	-0.0007
			(**0.00**)			(0.52)

Note: $RCS(\gamma_0)$ and $RCS(\gamma_1)$ are identification-robust confidence sets (CS) for the risk price, γ_1, of a non-tradable factor and the zero-beta rate, γ_0. $CS(\gamma_0)$ and and $CS(\gamma_1)$ are their respective conventional counterparts. Observations without brackets correspond to factor averages. Estimated Hotelling p-values are enclosed in round brackets; Mkt and Mkt^2 respectively denote factor return and its square expressed in excess of inflation.
* denotes significance at a 5% significance level attained if the factor mean falls outside of the corresponding CS. Beta pricing rule is defined as follows. For a tradable factor Mkt, there is a risk premium if its mean return is outside of the CS for γ_0; For a non-tradable factor Mkt^2, a risk premium exists if the factor average is not covered by the CS for γ_1.

Table 2.6: QCAPM (Treasuries and CMBS)

Period	**RCS**(γ_0)	**CS**(γ_0)	Mkt	**RCS**(γ_1)	**CS**(γ_1)	Mkt^2
Panel A: QCAPM - government bonds						
11/2004 - 11/2007	$\mathbb{R}$	{-0.0052, 0.0066}	0.0018	$\mathbb{R}$	{-0.0129, 0.0025}	-0.0018
			(0.07)			(0.83)
12/2007 - 06/2009	$\mathbb{R}$	{-0.0172, 0.0083}	0.0029	$\mathbb{R}$	{-0.0079, 0.0146}	-0.0012
			(0.85)			(0.75)
07/2009 - 12/2015	$]-\infty, -0.0041] \cup [-0.0030, +\infty[$	{-0.0021, 0.0050}	0.0013	$]-\infty, -0.0028] \cup [-0.0014, +\infty[$	{-0.0012, 0.0006}*	-0.0013
			(**0.02**)			(0.13)
11/2004 - 12/2015	$\mathbb{R}$	{-0.2756, 0.2405}	0.0017	$]-\infty, -0.0019] \cup [-0.0010, +\infty[$*	{-0.4140, 0.3581}	-0.0014
			(0.34)			(0.95)
Panel B: QCAPM - CMBS						
11/2004 - 11/2007	$\mathbb{R}$	{-0.0032, 0.0055}	0.0007	$\mathbb{R}$	{-0.0085, -0.0001}	-0.0019
			(0.44)			(0.67)
12/2007 - 06/2009	$\mathbb{R}$	{-0.0059, 0.0012}*	-0.0093	$\mathbb{R}$	{0.0013, 0.0400}	0.0035
			(0.17)			(0.39)
07/2009 - 12/2015	$\mathbb{R}$	{-0.0061, 0.0062}	0.0056	$]-\infty, -0.0037] \cup [-0.0011, +\infty[$*	{-0.0020, 0.0040}	-0.0012
			(**0.00**)			(0.33)
11/2004 - 12/2015	$\mathbb{R}$	{-0.0107, 0.0181}	0.0021	$]-\infty, -0.0054] \cup [0.0022, +\infty[$*	{-0.0737, 0.1382}	-0.0007
			(**0.00**)			(0.52)

Note: $RCS(\gamma_0)$ and $RCS(\gamma_1)$ are identification-robust confidence sets (CS) for the risk price, γ_1, of a non-tradable factor and the zero-beta rate, γ_0. $CS(\gamma_0)$ and and $CS(\gamma_1)$ are their respective conventional counterparts. Observations without brackets correspond to factor averages. Estimated Hotelling p-values are enclosed in round brackets; Mkt and Mkt^2 respectively denote factor return and its square expressed in excess of inflation.
* denotes significance at a 5% significance level attained if the factor mean falls outside of the corresponding CS. Beta pricing rule is defined as follows. For a tradable factor Mkt, there is a risk premium if its mean return is outside of the CS for γ_0; For a non-tradable factor Mkt^2, a risk premium exists if the factor average is not covered by the CS for γ_1.

Table 2.7: BCAPM and ΔFG funding liquidity factor

Period	**RCS(γ_0)**	**CS(γ_0)**	Mkt	**RCS(γ_1)**	**CS(γ_1)**	**ΔFG**
11/2004 - 11/2007	$\mathbb{R}$	{-0.0226, 0.0176}	0.0086	$\mathbb{R}$	{-7.9818, 12.5331}	0.0074
			(0.19)			(0.63)
12/2007 - 06/2009	$\mathbb{R}$	{-0.0014, 0.0021}*	-0.0209	$\mathbb{R}$	{-0.5603, -0.0411}*	-0.0219
			(**0.04**)			(0.21)
07/2009 - 12/2015	$\mathbb{R}$	{-0.2271, 0.1797}	0.0104	$]-\infty, -0.2583] \cup [0.3350, +\infty[$*	{-68.0492, 54.0750}	0.0039
			(**0.00**)			(0.64)
11/2004 - 12/2015	$\mathbb{R}$	{-0.0178, 0.0243}	0.0055	$]-\infty, -0.3309] \cup [0.4764, +\infty[$*	{-23.7713, 15.4947}	0.0012
			(**0.00**)			(0.47)

Table 2.8: BCAPM and PS liquidity factor

Period	**RCS(γ_0)**	**CS(γ_0)**	Mkt	**RCS(γ_1)**	**CS(γ_1)**	**PS**
11/2004 - 11/2007	$\mathbb{R}$	{-0.0068, 0.0044}*	0.0086	$\mathbb{R}$	{-0.1091, 0.4765}	0.0039
			(0.24)			(0.85)
12/2007 - 06/2009	$\mathbb{R}$	{-0.0014, 0.0023}*	-0.0209	$\mathbb{R}$	{-0.0263, 0.0815}*	-0.0351
			(**0.03**)			(0.23)
07/2009 - 12/2015	$\mathbb{R}$	{-0.0595, 0.0848}	0.0104	$]-\infty, -0.0562] \cup [0.0639, +\infty[$*	{-2.2866, 3.4291}	0.0149
			(**0.00**)			(0.17)
11/2004 - 12/2015	$\varnothing$	{-0.0014, 0.0017}*	0.0055	$\varnothing$	{0.0270, 0.1008}*	0.0048
			(**0.00**)			(**0.00**)

Note: $RCS(\gamma_0)$ and $RCS(\gamma_1)$ are identification-robust confidence sets (CS) for γ_1 and γ_0. $CS(\gamma_0)$ and and $CS(\gamma_1)$ are their respective conventional counterparts. Observations without brackets correspond to factor averages. Hotelling p-values are enclosed in round brackets; Mkt denotes real return on a stock market benchmark. ΔFG is the 1st difference for the funding liquidity factor of Fontaine and Garcia (2012). PS is the liquidity factor of Pástor and Stambaugh (2003).
* denotes significance at a 5% significance level attained if the factor mean falls outside of the corresponding CS. Beta pricing rule is defined as follows. For a tradable factor Mkt, there is a risk premium if its mean return is outside of the CS for γ_0; For non-tradable factors ΔFG and PS, a risk premium exists if the factor average is not covered by the respective CS for γ_1.

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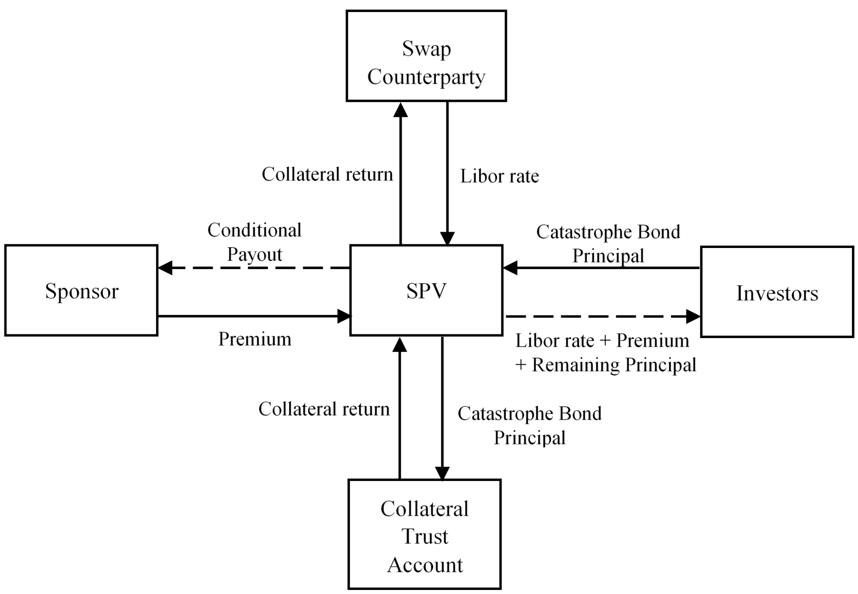
Appendices 2

A Catastrophe Bonds

Catastrophe bonds first emerged in mid-90s as an alternative way for the reinsurance markets to obtain risk capital for covering losses due to large-scale natural disasters. Through such a security, a sponsor issuing the bond transfers catastrophe risk to participants in financial markets. By the 2017, the market expanded considerably raising near US $30 billion in outstanding capital for the reinsurance markets (Artemis, 2017). Fast market development is largely due to the interest among investors to diversify their portfolios with securities exposed mainly to catastrophe risk. Given that fluctuations in financial markets do not trigger natural disasters, the latter is thought to be mostly unrelated to the systematic market risk.

Figure 2.A.1: Catastrophe bond design



Depicted in figure 2.A.1, the structure of a Catastrophe bond usually involves a party issuing the security, called a sponsor, and a Special Purpose Vehicle (SPV). The latter passes the catastrophe risk from the sponsoring party to investors in financial markets, manages collateral assets and payments to the parties. Once the SPV assumes the catastrophe risk through the agreement with the sponsor, the former distributes the risk among investors by issuing Catastrophe bonds in financial markets. Proceeds from selling Catastrophe bonds are stored in the form of a collateral which comprises of highly-rated financial securities. Unless a catastrophe-triggering default happens, investors are paid a principal at the bond expiry and regular coupons before that. A typical coupon payment comprises of a floating interest, e.g. LIBOR, plus a premium. Should the insured catastrophe occur before the Catastrophe bond matures, the latter defaults and its collateral is used for the payout to the sponsoring party.

Before the 2007-08 financial crisis, it was widespread to use the Total Return Swap counterparty (TRSC) to gain protection against movements in the interest rate and collateral value. The responsibility of the TRSC is to swap fixed returns on collateral assets for a floating interest rate and to bear loses that may result if there is a drop in the collateral value. Catastrophe bonds that have been issued more recently often avoid using the TRSC altogether, and instead rely on more stringent requirements for eligible collateral, systematic monitoring of the collateral account and frequent reporting to investors.

B Identification-robust method

To estimate an α-level identification-robust confidence set, $CS(\alpha,.)$, this paper relies on the method of Beaulieu, Dufour and Khalaf (2018) reproduced below.

The procedure builds on equations (2.8), (2.10) and (2.11) and the following structure assumed for the errors $U = [U_1, ..., U_n] = [Z_1, ..., Z_T]$:

$$Z_t = EW_t, \quad t = 1, \ \dots \ , \ T, \tag{B1}$$

with E being an full-column, unknown matrix. The distributional assumption on W_t requires a complete or partial specification. In the latter case, there could be one nuisance parameter. Gaussian-type confidence sets are obtained assuming that:

$$W_t \sim_{i.i.d.} N(0, I_n). \tag{B2}$$

The method requires splitting matrix $(X'X)^{-1}$ as follows:

$$(X'X)^{-1} = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \end{bmatrix}, \tag{B3}$$

The partitioned matrix consists of a scalar x_{11}, a $k \times 1$ vector $x_{21} = x_{12}'$ and a $k \times k$ matrix x_{22}, with $k = q + 1$.

Given this, inequality (2.17) needs to be restated in a quadratic form:

$$\dot{\lambda}' D_{22} \dot{\lambda} + 2D_{12}\dot{\lambda} + D_{11} \leq 0, \tag{B4}$$

where $D_{22} = \hat{b}\hat{S}^{-1}\hat{b}' - \frac{n}{d}F_{n,d,\alpha}x_{22}$, $D_{12} = D_{21}' = \hat{a}'\hat{S}^{-1}\hat{b}' - \frac{n}{d}F_{n,d,\alpha}x_{12}$, $D_{11} = \hat{a}'\hat{S}^{-1}\hat{a} - \frac{n}{d}F_{n,d,\alpha}x_{11}$, and $\hat{a}$, $\hat{b}$, $\hat{S}$ are OLS estimators as defined in (2.7) and (2.11).

Further, consider any $q \times 1$ non-zero vector ρ and let $\rho'\lambda$ denote a linear transformation of λ. Identification-robust confidence sets for any $\rho'\lambda$ are obtained using the analytical solution of Beaulieu, Dufour and Khalaf (2018) to the quadratic inequality in (B4). Their analytical formulas are based on the quadrics-based method of Dufour and Taamouti (2005) are are restated below.

Let $\tilde{D} = -D_{22}^{-1}D_{12}'$, $\quad \tilde{H} = D_{12}D_{22}^{-1}D_{12} - D_{11}$.

A closed or an empty confidence set results if every eigenvalue of D_{22} is above zero:

$$CS(\alpha, \rho'\lambda) = \left[\rho'\tilde{D} - \left(\tilde{H}\rho' D_{22}^{-1}\rho\right)^{1/2}, \quad \rho'\tilde{D} + \left(\tilde{H}\rho' D_{22}^{-1}\rho\right)^{1/2}\right], \quad if \quad \tilde{H} \geq 0 \tag{B5}$$

$$CS(\alpha, \rho'\lambda) = \varnothing, \quad if \quad \tilde{H} < 0 \tag{B6}$$

A union of two sets or a real line obtains when there is one negative eigenvalue for D_{22} and the latter is invertible:

(a) if $\rho' D_{22}^{-1}\rho < 0$ and $\tilde{H} < 0$:

$$CS(\alpha, \rho'\lambda) = \left]-\infty, \rho'\tilde{D} - \left(\tilde{H}\rho' D_{22}^{-1}\rho\right)^{1/2}\right] \cup \left[\rho'\tilde{D} + \left(\tilde{H}\rho' D_{22}^{-1}\rho\right)^{1/2}, +\infty\right[\tag{B7}$$

(b) if $\rho' D_{22}^{-1} \rho > 0$ or if $\rho' D_{22}^{-1} \rho \leq 0$ and $\tilde{H} \geq 0$:

$$CS(\alpha, \rho'\lambda) = \mathbb{R} \tag{B8}$$

(c) if $\rho' D_{22}^{-1} \rho = 0$ and $\tilde{H} \geq 0$:

$$CS(\alpha, \rho'\lambda) = \mathbb{R} \backslash \{\rho' \tilde{D}\} \tag{B9}$$

If there are at least two negative eigenvalues for D_{22} and the latter has full rank, the solution is a union of two sets.

C Conventional ML estimators

Conventional ML estimates for the zero-beta rate and risk prices are produced via an analytical solution of Beaulieu, Dufour and Khalaf (2018).

Given equations (2.8), (2.10) and (2.11), consider the following expression:

$$(X'X)^{-1} X'Y(Y'Y)^{-1} Y'X \tag{C1}$$

with the minimum non-zero root $\hat{\upsilon}$.

The ML estimator for λ is given by:

$$\hat{\lambda} = (\hat{p}\hat{S}^{-1}\hat{p}' - \hat{\upsilon} x_{22})^{-1} (\hat{p}\hat{S}^{-1}\hat{a} - \hat{\upsilon} x_{21}), \tag{C2}$$

$$\hat{p} = \begin{bmatrix} (\hat{b}_1 - \iota_n)' \\ \hat{b}_f \end{bmatrix},$$

where $\hat{a}$, $\hat{b}_1$, $\hat{b}_f$ $\hat{S}$ are OLS estimates given by (2.11). x_{22} and x_{21} are the elements of the matrix $(X'X)^{-1}$ as defined in (B3).

The computation of the asymptotic variance for $\hat{\lambda}$ involves a section of the information matrix that pertains to λ and b. The latter is estimated using the analytical formulas derived by Beaulieu, Dufour and Khalaf (2018) and reproduced below.

In particular, denote by $L(\lambda,\ b_1\ \ ...\ \ b_q\ , J)$ the Maximum Likelihood function. Estimating partial derivatives of the latter relative to $\lambda, b_1, ..., b_q$ and taking their negative expectations produces the following information sub-matrix $\Pi(\lambda,\ b_1\ \ ...\ \ b_q\ )$ and its inverse:

$$\Pi(\lambda,\ b_1\ \ ...\ \ b_q\ ) = \begin{bmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{bmatrix}, \quad \Pi(\lambda,\ b_1\ \ ...\ \ b_q\ )^{-1} = \begin{bmatrix} \Pi^{11} & \Pi^{12} \\ \Pi^{21} & \Pi^{22} \end{bmatrix},$$

with

$$\Pi_{11} = E\left(\frac{-\partial^2 L(\lambda,\ b_1 \quad ... \quad b_q\ , J)}{\partial\lambda\partial\lambda'}\right) = Tb\Psi^{-1}b'$$

$$\Pi_{22} = \left[E\left(\frac{-\partial^2 L(\lambda,\ b_1 \quad ... \quad b_q\ , J)}{\partial b_s \partial b_l'}\right)_{s,l=1,\ldots,q}\right] = (\boldsymbol{X} - \iota_T\lambda')' (\boldsymbol{X} - \iota_T\lambda') \otimes \Psi^{-1}$$

$$\Pi_{21} = \left[E\left(\frac{-\partial^2 L(\lambda,\ b_1 \quad ... \quad b_q\ , J)}{\partial b_s \partial\lambda'}\right)_{s=1,\ldots,q}\right] = T(\mu_X - \lambda) \otimes \Psi^{-1}b'$$

where ι_T denotes a $T \times 1$ vector of ones, $\Phi = JJ'$ and μ_x collects time series averages of factors in X in a q-dimensional column vector.

Given $\Phi_X(\lambda) = (\boldsymbol{X} - \iota_T\lambda')' (\boldsymbol{X} - \iota_T\lambda')/T$, the components of the inverse matrix are given by:

$$\Pi^{11} = \left(Tb\Psi^{-1}b'\right)^{-1}\left(1 - T(\mu_X - \lambda)' \Phi_X^{-1}(\lambda)(\mu_X - \lambda)\right)^{-1}$$

$$\Pi^{21} = \left(\left[-\Phi_X^{-1}(\lambda)(\mu_X - \lambda)\right] \otimes b'\right)\Upsilon^{11}$$

$$\Pi^{22} = \left[\Phi_X^{-1}(\lambda)/T \otimes \Psi\right] + \left(\left[\Phi_X^{-1}(\lambda)(\mu_X - \lambda)\right] \otimes b'\right)\Upsilon^{11}\left(\left[(\mu_X - \lambda)' \Phi_X^{-1}(\lambda)\right] \otimes b\right).$$

These formulas could be applied to compute analytically the asymptotic variance for the conventional estimator $\hat{\lambda}$.

D CGF test

Distributional assumption on disturbances is tested using the exact, multivariate CGF test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013). The latter is reproduced below for Gaussian errors.

The test statistic

The CGF test relies on the multivariate linear regression setting given by (2.8) and requires the following assumption on the errors $U = [U_1, ..., U_n] = [\Lambda_1, ..., \Lambda_T]$:

$$\Lambda_t = C\tilde{U}_t, \quad t = 1, \ \dots \ , \ T, \tag{D1}$$

where C is unknown and full-column and $\tilde{U}_t$ is either partially or completely specified. The former allows for one nuisance parameter. In Gaussian case:

$$\tilde{U}_t \sim_{i.i.d.} \mathcal{N}(0, I_n), \tag{D2}$$

The CGF test involves computing simulated p-values to assess whether (D2) holds true. The approach incorporates multivariate estimators of skewness and kurtosis (Mardia, 1970):

$$MS = \sum_{j=1}^{T}\sum_{t=1}^{T} \hat{g}_{jt}^3/T^2, \quad MK = \sum_{t=1}^{T} \hat{g}_{tt}^2/T, \tag{D3}$$

which sums over observations, $\hat{g}_{jt}$, retrieved from $\hat{G} = T\hat{U}(\hat{U}'\hat{U})^{-1}\hat{U}'$ and raised to a respective power. Note that $\hat{U}$ contains OLS residuals as defined in (2.11). Beaulieu, Dufour and Khalaf (2003, 2007, 2013) show that the distributions of MS and MK are pivotal. In particular, consider the two measures

$$g_S = \sum_{j=1}^{T}\sum_{t=1}^{T} g_{jt}^3/T^2, \quad g_K = \sum_{t=1}^{T} g_{tt}^2/T, \tag{D4}$$

constructed using the elements, g_{jt}, from the array

$$G = TL\tilde{U}(\tilde{U}'L\tilde{U})^{-1}\tilde{U}'L, \quad \tilde{U} = \left[\tilde{U}_1, \ \dots \ , \tilde{U}_T\right]', \quad L = I - X(X'X)^{-1}X'. \tag{D5}$$

The distributions of g_S and g_K are pivotal. This follows since $\tilde{U}$ is Gaussian and G is nuisance-parameter free. Beaulieu, Dufour and Khalaf (2003, 2007, 2013) show that MS and g_S have the same distributions. The same distributional result holds between MK and g_K. It implies pivotal distributions for MK and MS.

For the CGF test, MK and MS measures are expressed in deviation from their simulation-based expected values $\overline{MS}$ and $\overline{MK}$:

$$E_{MS} = |MS - \overline{MS}|, \quad E_{MK} = |MK - \overline{MK}| \tag{D6}$$

Pivotality of the underlying measures transfers over to E_{MS} and E_{MK}. This allows to produce the corresponding exact p-values, $\hat{p}_N(E_{MS})$ and $\hat{p}_N(E_{MK})$, as per steps outlined in E.2.1-E.2.4 that involve an application of the Monte Carlo (MC) method (Dufour, 2006; Dwass, 1957; Barnard, 1963).

The individual p-values are further combined to produce the CGF test statistic:

$$E_{MSK} = 1 - min\{\hat{p}_N(E_{MS}), \hat{p}_N(E_{MK})\} \tag{D7}$$

Following steps E.3.1-E.3.8, the exact MC p-value could be estimated for E_{MSK}.

MC method

In this part of the appendix, we outline the MC method of Dwass (1957); Barnard (1963); Dufour (2006). In the setting defined by equations (2.8), (D1) and (D2), the MC method builds on the test statistics $V(Y, X)$. The latter is pivotal in the sense that there exist a following transformation under the null hypothesis:

$$V(Y, X) = \dot{V}(\tilde{U}, X).$$

Let $V^{(0)}$ signify the value of this statistic obtained given the collected dataset. Its exact p-value, $\hat{p}_Q[V] = p_Q[V^{(0)}, V]$, is given by the following MC formula:

$$p_Q[h, V] \equiv \left(1 + \sum_{q=1}^{Q} I_+ \left[V^{(q)} - h\right]\right) / (1 + Q) \tag{D8}$$

$$I_+ \left[V^{(q)} - h\right] = \begin{cases} 1, & \text{if } \left[V^{(q)} - h\right] \geq 0, \\ 0, & \text{if } \left[V^{(q)} - h\right] < 0. \end{cases}$$

where the statistic $V^{(q)}$ is obtained via a simulation given the q-th replication of Q $i.i.d.$ draws from $\tilde{U}$, $\tilde{U}_{(q)} = \left[\tilde{U}_1^{(q)}, \ \ldots \ , \tilde{U}_n^{(q)}\right]$, $q = 1, \ \ldots \ , \ Q$.

Range $\hat{p}_Q[V] \leq \alpha$, $0 < \alpha < 1$, corresponds to the MC exact critical region. For integer values of $\alpha(1 + Q)$, the $\hat{p}_Q[V]$ is exact under the null hypothesis in the following sense

$$P[\hat{p}_Q[V] \leq \alpha] = \alpha, \tag{D9}$$

when V has a continuous distribution.

E Implementation of the CGF test

The CGF test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013) comprises of three parts summarized in E.1.1 - E.3.8.

Simulated moments

E.1.1 Construct $\tilde{N}$ matrices given by:

$$G_{(j)} = TL\dot{\tilde{U}}_{(j)}(\dot{\tilde{U}}'_{(j)}L\dot{\tilde{U}}_{(j)})^{-1}\dot{\tilde{U}}'_{(j)}L, \quad L = I - X(X'X)^{-1}X', \quad j = 1, \ \ldots \ , \ \tilde{N}, \tag{E1}$$

where $\dot{\tilde{U}}_{(j)}$ is one out of $\tilde{N}$ *i.i.d.* replications retrieved from $\tilde{U}$ in j-th order. At each draw j, use $G_{(j)}$ to compute values of skewness $MS_{(j)}$ and kurtosis values, and $MK_{(j)}$, $j = 1, ..., \tilde{N}$. according to (D3). In total, there are $\tilde{N}$ simulation-based estimates to be produced for each moment measure.
E.1.2 Averaging simulated moments across $\tilde{N}$ realizations produces their simulation-based expectations:

$$\overline{MS} = \tilde{N}^{-1} \sum_{J=1}^{\tilde{N}} MS_{(j)}, \quad \overline{MK} = \tilde{N}^{-1} \sum_{J=1}^{\tilde{N}} MK_{(j)}, \quad j = 1, ..., \tilde{N}. \tag{E2}$$

Skewness and kurtosis tests

E.2.1 Consider the expected skewness and kurtosis values simulated as in E.1.1-E.1.2. Use these and the observed data to estimate excess moments $E^{(0)} = [E^{(0)}_{MS}, E^{(0)}_{MK}]'$ according to (D6).
E.2.2 Draw K times from $\tilde{U}$ to produce *i.i.d.* realizations numbered $i = 1, \ldots, K$. Given (D6), use each simulated sample i to generate the corresponding estimates of the excess moments $E_{(i)} = [E^{(i)}_{MS}, E^{(i)}_{MK}]'$. To compute the latter, plug in the same simulation-based expectations of moments as those used for $E^{(0)}$.
E.2.3 Produce exact MC p-values for the excess moments, $\hat{p}_K[MS]$ and $\hat{p}_K[MK]$, according to (D8). The α-level rejection rule is $\hat{p}_K[MS] \leq \alpha$ for the skewness test and $\hat{p}_K[MK] \leq \alpha$ for testing kurtosis.
E.2.4 When E is continuously distributed, the following holds for each test given the exchangeability of $E_{(i)}$, $i = 1, \ldots, K$:

$$P[\hat{p}_K[MS] \leq \alpha] = P[\hat{p}_K[MK] \leq \alpha] = \alpha \quad \textit{under the null hypothesis}$$

Combined test

E.3.1 Follow steps in E.1.1-E.1.2 to estimate values of expected moments based on simulated samples. Using the latter expectations, produce K simulation-based excess skewness and kurtosis estimates according to E.2.2.
E.3.2 Based on K simulated excess moment statistics from the previous step, construct the associated MC p-value functions of the form (D8), denoted by $p_K[h, V]$ for $C = E_{MS}, E_{MK}$.
E.3.3 Denote the excess moments obtained with the collected dataset as $E^{(0)} = [E^{(0)}_{MS}, E^{(0)}_{MK}]'$. Using expected moments simulated in E.3.1, produce the latter as described in E.2.1.
E.2.4 Produce K_1 simulated samples by retrieving *i.i.d.* realizations from $\tilde{U}$ while preserving the integer value of $\alpha(K_1 + 1)$.
E.3.5 Plug into (D6) expected moments from E.3.1 and observations from the K_1 simulated samples obtained in the last step to obtain K_1 simulated estimates of excess skewness and

kurtosis: $E^{(s)} = [E_{MS}^{(s)}, E_{MK}^{(s)}]'$, $s = 1, \ldots, K_1$.

E.3.6 Revisit the MC p-value functions produced in E.3.2. Applying the latter to $E^{(0)}$ and $E^{(s)}, s = 1, \ldots, K_1$, obtain the associated size-correct p-values: $\hat{p}_K^{(0)}(V) = p_K(V^{(0)}; V)$ and $\hat{p}_K^{(s)}(V) = p_K(V^{(s)}; V)$, $s = 1, \ldots, K_1$ with $V = E_{MS}, E_{MK}$.

E.3.7 Given the p-values obtained in the last step, the CGF test statistic is given by:

$$E_{MSK}^{(m)} = 1 - min\{\hat{p}_K(E_{MS}^{(m)}), \hat{p}_K(E_{MK}^{(m)})\}, \quad m = 0, 1, 2 \ldots, K_1. \tag{B.18}$$

E.3.8 Plug in observations $E_{MSK}^{(m)}$, $m = 0, 1, 2 \ldots, K_1$ into (D8) to yield the MC p-value for the CGF test, $\hat{p}_{K_1}[E_{MSK}]$. The rejection of the null hypothesis occurs at a level α if $\hat{p}_{K_1}[E_{MSK}] \equiv p_{K_1}[E_{MSK}^{(0)}, E_{MSK}] \leq \alpha$. Under the null hypothesis, $E_{MSK}^{(m)}$, $m = 0, 1, 2 \ldots, K_1$ satisfy the exchangiability property. Given the latter, the size of the CGF test is always α.

Chapter Three

An alpha and risk analysis of Catastrophe bond mutual funds: exact, simultaneous inference

3.1 Introduction

Launched nearly two decades ago, Catastrophe bond mutual funds [**CBMFs**] offer an investment in a mixture of diverse Catastrophe bonds that pay coupons and principal if no default-triggering catastrophe, like tornado or earthquake, takes place. These funds aim to deliver "... a stable return that is higher than the risk-free interest rate, with a low correlation to fluctuations in financial markets" (LGT Capital Partners, 2015).[1] Formally, such marketing claims suggest that CBMFs could produce a positive alpha, i.e. an additional return over the risk-free benchmark and have small factor betas in the sense that they display low co-movement with the usual financial market benchmarks. The latter property is particularly appealing to investors as it allows to diversify away some of the systematic risk on a larger investment portfolio. The focus of this paper is to formally examine whether CBMFs generate a positive alpha and the extent of their sensitivity to the developments in financial markets.

It is of importance to study CBMFs formally for a number of reasons. First, lacking reliable information about funds' performance, investor expectations about future returns may diverge considerably from the actual fund valuations, thus making the financial system vulnerable to rapid price corrections and less resilient. The impact of this vulnerability could be quite pronounced given that nearly US $30 billion in Catastrophe bonds were outstanding in 2017 with CBMFs capturing the dominant 60% share of all new issues (Artemis, 2017; Aon Benfield, 2017b). Second, serious social costs could arise if investor savings are mismanaged due to unreliable performance information. Third, as a primary investor in newly-issued Catastrophe bonds, CBMFs represent an important source of funding for reinsurance markets. Globally, 30% of risk capital raised through alternative sources for property catastrophe reinsurance in 2017 originated from Catastrophe bonds (Aon Benfield, 2017a). Thus, an impaired market for CBMFs could undermine the stability of reinsurance markets. Offering empirical evidence on the performance of CBMFs could aid investors in organizing their savings and help strengthen the resilience of financial and reinsurance systems.

Although relevant, the issue of whether CBMFs can deliver a positive alpha has yet to

[1] See Appendix A for a more detailed description of Catastrophe bonds.

be formally studied. Also, little formal evidence is available in this regard for Catastrophe bonds and indices (as opposed to funds). To our best knowledge, only Bantwal and Kunreuther (1999) examine risk-adjusted returns on selected Catastrophe bonds using their Sharpe ratios. In addition, research on the dynamics between CBMFs and financial markets remains scarce. For the period before the mid-2008, Cummins and Weiss (2009) perform a pooled regression on CBMFs to formally examine factor loadings on stock and corporate bond benchmarks. Albeit positive and statistically significant, estimated factor coefficients are economically small suggesting a fairly little co-movement between CBMFs and financial markets till the mid-2008. In a related strand of the literature on Catastrophe bonds and indices, several studies provide evidence on factor loadings or correlations with respect to financial market benchmarks (see Cummins and Weiss, 2009; Carayannopoulos and Perez, 2015; Gürtler, Hibbeln and Winkelvos, 2014; Gomez and Carcamo, 2014; Braun, 2015). Overall, their findings suggest that, albeit not quite zero-beta,[2] Catastrophe bonds display a fairly modest sensitivity to the fluctuations in financial markets.

Compared to available literary works, this study adds in four respects. First, we assemble exact, simultaneous confidence sets for cross-sectional coefficients in the Multivariate Linear Regression [**MLR**] model with CBMFs. This proceeds in a multivariate Least-Squares setting and relies on the method of Beaulieu, Dufour and Khalaf (2018). Set estimates for intercepts are then applied for a joint inference on the alpha of CBMFs, while those for factor loadings are used to assess the beta risk against each benchmark. To the extent that our analysis of risk exposures and the alpha relies respectively on factor loadings and intercepts, we follow the approach common in the literature (for instance, see Jensen, 1968; Connor and Korajczyk, 1986; Grauer, 2008; Kan and Wang, 2017; Fama and French, 1993; Cummins and Weiss, 2009; Gürtler, Hibbeln and Winkelvos, 2014; Gomez and Carcamo, 2014). In contrast to the single-parameter approach, this study evaluates cross-sectional coefficients jointly via the size-correct procedure. Such a joint assessment allows to draw inference about the overall performance of CBMFs in terms of their betas and alpha.

In particular, the method used in the set construction proceeds by inverting the Hotelling test (Hotelling, 1947) defined for a cross-section of either intercepts or loadings on a given risk factor. The inversion procedure produces intervals that contain only parameter values for which the cross-sectional coefficients are jointly insignificant at a chosen level α. The inversion relies on the analytical solution thus avoiding costly grid searches as is common in the identification-robust literature. All cross-sectional set estimates are assembled concurrently and share a common probability of parameter coverage

[2] A zero-beta characteristic is typically ascribed to an asset that does not fluctuate with financial markets.

that holds with the $(1-\alpha)$ confidence level given any number of sample observations. This assures that resulting confidence sets are exact and simultaneous. Relative to the exact, joint significance test on intercepts of Gibbons, Ross and Shanken (1989) [**GRS**] and its counterpart for factor betas, exact, simultaneous confidence sets are more informative. Unlike the GRS-type test which is defined for a specific parameter value, set estimates incorporate the information from assessment of multiple parameter values retaining only those that were not rejected (see Lewellen, Nagel and Shanken, 2010; Beaulieu, Dufour and Khalaf, 2018). The latter could help avoid the possibility of an insignificant test specified for a single value to be mis-construed. This highlights the benefits of relying on simultaneous confidence sets rather than a joint significance test for inference on factor betas and alpha.[3]

Second, we extend the method of Beaulieu, Dufour and Khalaf (2018) that produces exact, simultaneous confidence sets for cross-sectional MLR coefficients to a setting with jointly multivariate Student-t errors and apply the extended procedure for the inference on the beta risk and the alpha of CBMFs. In particular, test inversion in a Least-Squares setting involves a Fisher-based cut-off point given that the null distribution of the Hotelling statistic is Fisher. With Student-t errors, however, the null distribution of the test statistic, while retaining its invariance to nuisance parameters, becomes non-standard. To assemble exact, simultaneous confidence sets for MLR coefficients in a Student-t case, we propose to replace the Fisher-based cut-off point with the one obtained by simulating the null distribution for the Hotelling statistic.[4] Given that the pivotality of the latter is preserved in the Student-t setting, confidence sets produced with the simulated cut-off point remain simultaneous and exact for any sample size. Most importantly, the analytical solution is preserved and no grid searches are needed despite the non-Gaussian framework.

To the extent that CBMFs mainly comprise of catastrophe-linked securities and given the empirical evidence suggesting that the distributions of financial returns are oftentimes more thick-tailed as compared to the Gaussian case (see, e.g., Richardson and Smith, 1993), the latter could be too restrictive for the model with CBMFs. Student-t setting may be better suited for the analysis of CBMFs. As such, we use the extended approach for the model with CBMFs to produce simulation-based confidence sets for cross-sectional coefficients under *i.i.d.* jointly multivariate Student-t(η) errors to inform on the beta risk

[3]Simultaneous inference has been considered in multiple other contexts. These include simultaneous confidence regions for impulse response functions and for path forecast analysis (Jordà, 2009; Jordà and Marcellino, 2010), simultaneous confidence set estimation on parameter ratios (Bolduc, Khalaf and Yélou, 2010), identification-robust, simultaneous procedures for the zero-beta rate and risk prices in asset pricing models (Beaulieu, Dufour and Khalaf, 2015, 2018), simultaneous confidence bands for parameter vectors (Montiel Olea and Plagborg-Møller, 2018).

[4]This extends Beaulieu, Dufour and Khalaf (2007, 2010) from testing to a confidence set context.

and alpha.

Third, we assess CBMFs in terms of their beta risk and the alpha against several well-known benchmarks. These include a single-factor benchmark based on the traditional Capital Asset Pricing Model [**CAPM**] (Sharpe, 1964; Lintner, 1965*a*,*b*; Jensen, 1968) and its extended two-factor version, the Quadratic CAPM [**QCAPM**]. In addition to the traditional excess market return as in the CAPM, the extended QCAPM benchmark also incorporates a mimicking portfolio for its squared return as a second factor. Barone-Adesi (1985), and more recently, Barone-Adesi, Gagliardini and Urga (2004), provide the Arbitrage Pricing Theory [**APT**] and the empirical motivation for capturing the market coskewness risk via the beta on a mimicking portfolio for the squared market return. The theory of an investor preference for the positive market coskewness can be traced back to Kraus and Litzenberger (1976) and their Three Moment CAPM, which expresses expected asset returns as a linear combination of coskewness and market betas. In addition, to the extent that CBMFs are related to extreme events, there could be a non-linear relationship between these funds and financial markets. Through the squared market return, QCAPM also allows to account for the non-linear dynamics.

Further, CBMFs are also assessed with respect to the three-factor Fama-French benchmark (Fama and French, 1993) with the excess market return, Small-minus-Big (SMB) and High-minus-Low (HML) portfolios. The last two of these mimic factors cover additional sources of systematic risk associated with firm characteristics such as a size and a book-to-market value. As argued by Harvey and Siddique (2000), SMB and HML factors could mimic for the market coskewness as they may be capturing the same non-diversifiable risks.

Fourth, we provide results on the beta risk and alpha of CBMFs obtained in the context of the 2011 Tohoku earthquake in Japan. To the extent that risks underlying CBMFs are linked to the occurrence of natural disasters, these assets differ from traditional securities like stocks and bonds and could perform differently following a large-scale, exogenous catastrophic event. This motivates a closer examination of CBMFs in a context of the Tohoku earthquake that struck Japan in 2011. Being the largest in the history of Japan, this earthquake caused a devastating tsunami resulting in an enormous economic and humanitarian crisis. The disaster set off the default of the "Muteki" Catastrophe bond with investors loosing the entire principal of USD $300 million as a consequence (PLENUM Insurance Linked Capital, 2011). For comparison, while the 2005 hurricane Katrina, the costliest and one of the deadliest hurricanes in the US, also triggered the default of Kamp Re Catastrophe bond, the losses to its investors were less severe as they recovered USD $45 million out of USD $190 million of principal upon bond maturity (Artemis, Deal Directory - Cat Bonds & ILS, n.d.). Given this and the pronounced impact of the Tohoku earthquake on CBMFs that saw their prices plummet to the record low levels, it is pertinent to conduct a sub-sample analysis of these funds in the context of the 2011 Tohoku earthquake.

Empirically, several results are of particular interest. First, our sub-sample analysis provides the evidence of a positive alpha on CBMFs after the 2011 Tohoku earthquake as most funds have confidence sets for the intercepts that cover strictly positive values. This is robust across CAPM, QCAPM and Fama-French benchmarks and maintained both in Gaussian and Student-t settings. Second, empirical findings overall suggest that even if factor betas exceed zero, the risk exposure of CMBFs would be moderate given that the upper set bounds, albeit positive, are fairly small. This result holds across factors and sub-periods and is consistent with the economically small factor betas reported for CBMFs by Cummins and Weiss (2009). Third, to the extent that confidence sets for all loadings on each factor also contain values equal and below zero, there is a possibility that CBMFs are zero-beta or even negative-beta assets and as such could be useful for diversification of risk on a larger investment portfolio.

The rest of the paper has the following structure. The model and the empirical strategy are outlined in the subsequent section. Section 3.3 details the methodological approach. The data and results of our empirical investigation are presented, accordingly, in sections 3.4 and 3.5. Conclusion follows in section 3.6.

3.2 The model and the empirical strategy

The analysis builds on the following MLR model with n mutual funds and T time periods (see, e.g., Jensen, 1968; Connor and Korajczyk, 1986):

$$r_t = a + b'F_t + u_t, \quad t = 1, ..., T, \tag{3.1}$$

where r_t and R_t are respectively $n \times 1$ and $q \times 1$ vectors of returns on n mutual funds and q risk factors observed at time t. Each variable is net of the risk-less rate. Also, $a = (a_1, ..., a_n)'$ is a $n \times 1$ vector that collects intercepts, while the $q \times n$ matrix of factor loadings on q risk factors is given by:

$$b = \begin{bmatrix} \beta_1' \\ \beta_2' \\ \vdots \\ \beta_q' \end{bmatrix}, \quad \beta_j = (b_{1j}, ..., b_{nj})', \quad j = 1, ..., q. \tag{3.2}$$

Further, u_t is a time-t column vector assembling disturbances for n funds.

For a joint inference on alphas, the empirical strategy relies on exact, simultaneous confidence sets assembled for the cross-sectional intercepts, a. Producing the confidence sets requires inversion of the Hotelling test defined for the following joint null hypothesis:

$$H_0^{(1)} : a = \bar{a}, \quad \bar{a} \textit{ is known.} \tag{3.3}$$

Inference on the alphas proceeds by checking whether the resulting confidence sets for the intercepts contain only values above zero.

A similar approach is used to assess jointly risk sensitivities on each of the q factors. For this purpose, we build exact, simultaneous confidence sets for n cross-sectional loadings for each factor j collected in β_j. This involves the following joint null hypothesis:

$$H_0^{(2)} : \beta_j = \bar{\beta}_j, \quad \bar{\beta}_j \textit{ is known}, \quad j \in \{1, \dots, q\}, \tag{3.4}$$

and an inversion of the associated Hotelling test.

The estimation of exact, simultaneous confidence sets for the cross-sectional MLR coefficients proceeds analytically using the method of Beaulieu, Dufour and Khalaf (2018) in the Gaussian setting and its extension in the Student-t case detailed in the next section.

Using a matrix notation, the model in (3.1) could be restated as

$$Y = X\Theta + U, \tag{3.5}$$

such that Y is a $T \times n$ matrix gathering all mutual fund returns, U is a $T \times n$ matrix assembling errors and $X = [\iota_T, F]$ is full-column $T \times k$ matrix with a column of ones, ι_T, and a $T \times q$ array of excess returns on q risk factors such that $k = q + 1$ and:

$$Y = \begin{bmatrix} r_1' \\ \vdots \\ r_T' \end{bmatrix}, \quad U = \begin{bmatrix} u_1' \\ \vdots \\ u_T' \end{bmatrix}, \quad F = \begin{bmatrix} F_1' \\ \vdots \\ F_T' \end{bmatrix} = \left[\tilde{F}_1, ..., \tilde{F}_q\right], \quad \tilde{F}_j = (\tilde{F}_{j1}, ..., \tilde{F}_{jT})', \quad j = 1, ..., q.$$

Also, Θ is a $k \times n$ matrix comprising of all MLR coefficients, that is

$$\Theta = \begin{bmatrix} a' \\ b \end{bmatrix} = \begin{bmatrix} \theta_1' \\ \theta_2' \\ \vdots \\ \theta_k' \end{bmatrix}, \quad \theta_s = (\theta_{1s}, ..., \theta_{ns})', \quad s = 1, ..., k, \tag{3.6}$$

where θ_s collects n cross-sectional coefficients on a regressor s and, thus, comprises of either intercepts or loadings on one of the risk factors.

Given the general model in (3.5), the joint null hypothesis on its cross-sectional coefficients for a single regressor is given by:

$$H_0^{\theta_s} : \theta_s = \bar{\theta}_s, \quad \bar{\theta}_s \textit{ is known}, \quad s \in \{1, \dots, k\}, \tag{3.7}$$

which for $s = 1$ reduces to the restriction on intercepts defined in (3.3), while for $s > 1$ corresponds to the restriction on cross-sectional loadings for one of the risk factors as stated in (3.4).

The next section describes the procedure for producing exact, simultaneous confidence sets for the parameters in θ_s, $s = 1, ..., k$ under different distributional assumptions.

In the rest of the paper, let

$$\hat{\Theta} = (X'X)^{-1}X'Y = \begin{bmatrix} \hat{\theta}_1' \\ \hat{\theta}_2' \\ \vdots \\ \hat{\theta}_k' \end{bmatrix}, \quad \hat{\theta}_s = (\hat{\theta}_{1s}, ..., \hat{\theta}_{ns})', \quad s = 1, ..., k, \tag{3.8}$$

$$\hat{U} = Y - X\hat{\Theta}, \quad \hat{S} = \hat{U}'\hat{U},$$

denote respectively OLS estimator of Θ, residuals and their squared sum defined for the model in (3.1).

3.3 Methodological approach

To construct exact, simultaneous confidence sets for components of $\theta_s,\ s \in \{1, \ \ldots \ , \ k\}$, in a Gaussian setting, we use the method of Beaulieu, Dufour and Khalaf (2018). This involves the following Hotelling test statistic defined for the joint null hypothesis in (3.7):

$$\Psi(\bar{\theta}_s) = \frac{(\hat{\theta}_s - \bar{\theta}_s)'\hat{S}^{-1}(\hat{\theta}_s - \bar{\theta}_s)}{\rho_k[s]'(X'X)^{-1}\rho_k[s]} \frac{d}{n}, \tag{3.9}$$

where $\bar{\theta}_s$ is a vector of specific values of θ selected from the admissible set $\Gamma = \mathbb{R}^k$ and $\rho_k[s]$ is a $k \times 1$ vector collecting zeros and a single positive value in row s equal to one.

The null distribution of $\Psi(\bar{\theta}_s)$ is given by:

$$\Psi(\bar{\theta}_s) \sim G(n, d) \quad d = T - k - n + 1, \quad under\ H_{\theta_s}, \tag{3.10}$$

where $G(n, d)$ denotes a Fisher distribution provided that errors are $i.i.d.$ jointly multivariate Normal.

The estimation of exact, simultaneous confidence sets for θ_s requires using the statistic in (3.9) to invert the following Hotelling test:

$$\Psi(\bar{\theta}_s) \leq g_{n,d,\alpha} \quad d = T - k - n + 1, \tag{3.11}$$

where α is a significance level and $g_{n,d,\alpha}$ is the associated cut-off point recovered from the Fisher distribution when the errors are Gaussian. The test inversion searches over all admissible values of θ_s one at a time. For each particular choice $\bar{\theta}_s$, the associated value of the test statistic $\Psi(\bar{\theta}_s)$ is computed given (3.9). By retaining only those parameter values for which inequality (3.11) is satisfied at a significance level α, an exact, joint confidence region for θ_s is produced. The procedure attains at least $(1 - \alpha)$ confidence level for the resulting joint region. In other words, the latter has the probability of a parameter inclusion that is joint over all components of θ and is no less than $(1 - \alpha)$. Locating the minimum and the maximum values for each parameter within the joint region further allows to extract exact, simultaneous confidence sets for individual components of θ. The method of Beaulieu, Dufour and Khalaf (2018) implements all these steps analytically via the formulas that they derive based on the quadrics approach of Dufour and Taamouti (2005). These formulas are restated in the Appendix B.

Extending the approach of Beaulieu, Dufour and Khalaf (2018), initially proposed in a Gaussian setting, to a Student-t case, we propose to replace the Fisher-based cut-off point with the simulated one. Specifically, when the errors are jointly multivariate Student-t($\bar{\eta}$), where $\bar{\eta}$ denotes a known number for the degrees of freedom, the null distribution $G(n, d)$ for the Hotelling statistic $\Psi(\bar{\theta}_s)$ is no longer standard, but remains pivotal. Given this, $G(n, d)$ could be simulated in order to obtain an α-level simulation-based cut-off point for the test inversion. The procedure for the latter is outlined in the Appendix C. Building exact, simultaneous confidence sets for cross-sectional MLR coefficients under Student-t($\bar{\eta}$) errors then involves using the analytical solution of Beaulieu, Dufour and Khalaf (2018) modified to apply the simulation-based critical point instead of its Fisher-based counterpart. Importantly, the analytical solution still applies in the Student-t setting as the distribution of $\Psi(\bar{\theta}_s)$, and in turn the simulated cut-off point, does not depend on $\bar{\theta}_s$.

Given that cash flows on CBMFs depend on whether a qualified catastrophe strikes or not, it may be more appropriate to assess these funds in the setting with disturbances that follow a distribution with wider tails than in the Gaussian case. The Student-t version of the method of Beaulieu, Dufour and Khalaf (2018) allows to examine CBMFs allowing for more extreme distributional tails (relative to Gaussian setting) for the error terms. In addition, previous empirical research also shows that financial assets tend to deviate from normality (see,e.g., Fama, 1965; Officer, 1972; Richardson and Smith, 1993). As such, the method of Beaulieu, Dufour and Khalaf (2018) extended to a Student-t case can be also applied to assess other financial assets besides CBMFs.

Irrespective of whether the errors are jointly multivariate Student-t($\bar{\eta}$) or Gaussian, resulting set estimates for components of θ are exact, or size-correct, and simultaneous. This occurs as the probability of parameter inclusion is maintained over all confidence sets at the confidence level of $(1 - \alpha)$ regardless of how many observations are in the sample (n or T).

Applying the extended method of Beaulieu, Dufour and Khalaf (2018) to the MLR model with CBMFs, we also estimate exact, simultaneous confidence sets for cross-sectional coefficients on each regressor in a Student-t($\bar{\eta}$) setting and use these for the inference on the beta sensitivity and the alpha.

3.4 Data

In this study, CBMFs are analyzed over the two sub-periods: 11/2004-03/2011 and 04/2011-12/2015. The analysis relies on the returns for seven CBMFs computed by taking the natural log difference of fund prices retrieved from Bloomberg. These returns are stated as a spread above the risk-less rate given by the one-month Treasury Bill rate downloaded from the Wharton Research Data Services (WRDS). CBMFs that we use are displayed in the Table 3.1 with their excess returns plotted in Figures 3.1 and 3.2.

On the factors side, we use the basket of all equities traded on NYSE, AMEX and Nasdaq to proxy for the traditional market portfolio in every specification. For the analysis, its value-weighted return (ticker VWRETD), retrieved from the Center for Research in Security Prices (CRSP), is expressed in excess of the risk-free interest rate (same as for CBMFs).

In the QCAPM benchmark, we also use the mimicking portfolio for the squared market return obtained by projecting the latter on benchmark asset returns (over the risk-less rate). The latter include returns on the momentum factor and six Fama-French portfolios (sorting on the market capitalization and book-to-market), which we retrieve from the online Kenneth French Data Library. As an additional base asset, these are complemented with the US Treasury 10-year government bond yield (ticker USGG10YR) from Bloomberg. More details about the construction of a mimicking portfolio for the squared market return are provided in the Appendix F. The Fama-French benchmark considered in the analysis also incorporates the HML and SMB portfolio returns downloaded from the Kenneth French Data Library.

3.5 Empirical Results

3.5.1 Descriptive Statistics

The objective of this section is to summarize the data in terms of its sample moments and to provide the results of the distributional tests.

The excess returns on CBMFs and all risk factors are described through their mean, variance, skewness and kurtosis in the Table 3.4. The first seven rows display the summary statistics for CBMFs with the rest of the table providing estimates for the risk factors.

For CBMFs, there is a considerable difference between the two sub-periods in terms of the first four sample moments. During the first sub-period covering the 2007-08 financial crisis, all CBMFs returns are considerably lower, even negative for some funds, more volatile and display a high degree of excess skewness and kurtosis. The latter metrics are also elevated over the full sample, albeit mean fund returns are all positive over the long-run. After March 2011, returns on all funds become higher, are all positive, vary less and have little excess skewness and kurtosis.

For risk factors, the sample moments up to the fourth order also vary across the two sub-periods. The volatility is higher while excess kurtosis and negative skewness are more pronounced across all factors in the first period, but subside thereafter. Mean values for the market return and the portfolio that mimics its square rise over time between the two sub-periods. SMB and HML mean returns become lower after March 2011. In all periods, market return varies the most, HML has the largest degree of excess skewness while the mimicked squared return has the greatest mean across risk factors.

In terms of correlations displayed in the Table 3.5, there is a positive relationship among CBMFs, which is stronger during the 1st sub-period covering the 2007-08 financial crisis. Estimated correlations among CBMFs are also positive and pronounced over the full sample. All risk factors are positively related to each CBMFs in the first sub-period and over the long run. After March 2011, market return and the mimicking portfolio for its square mostly have an inverse relationship with funds, while HML returns continue to co-move positively with all CBMFs. In absolute terms, correlation estimates between the market return and CBMFs are greater in the first sub-period indicating a higher degree of co-movement.

We also describe findings from the distributional tests on disturbances in the model (3.5). Table 3.2 reports estimated p-values for the Combined Goodness-of-Fit (CGF) test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013). The latter is defined for a joint null hypothesis imposing Gaussian values of skewness and kurtosis on the error distribution. The steps for performing the CGF test are restated in the Appendices D and E. For each benchmark, the normality is rejected at the 5% significance level in every period.

In addition, we test whether errors are Student-t using the CGF test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013). This builds on a joint null hypothesis that restricts skewness and kurtosis values to their equivalents from the $i.i.d.$ multivariate Student-t($\bar{\eta}$) distribution with $\bar{\eta}$ indicating a particular selection for the degrees of freedom. Looping over admissible values for η, the CGF test is conducted for each specific choice $\bar{\eta}$ at the α level of significance. Collecting all the values $\bar{\eta}$ for which the rejection of the joint null hypothesis on the errors does not occur yields a $(1-\alpha)$ confidence set for η. These are reported in the Table 3.3 at a 5% significance level. The results are homogeneous across all benchmarks. Notably, the Student-t(η) distribution is not rejected for the case with 2 degrees of freedom in the first sub-period and for a range of η values between 2 and 6 thereafter.[5] Over the full sample the Student-t(η) distribution is also not rejected for η equal 2. As the next section shows, despite evidence of extreme thick tails, the set estimates for MLR coefficients obtained under different distributional assumptions are quite similar, and switching from Gaussian to Student-t setting does not affect the inference on the risk sensitivity and alpha of CBMFs.

[5] In the 1st sub-period, Cauchy distribution is also not rejected, which implies highly skewed errors.

3.5.2 Regression Results

In this section, we report findings from the MLR analysis conducted for CBMFs against CAPM, QCAPM and Fama-French benchmarks. Results for the latter models are available respectively in Tables 3.6 through 3.8. In each table, Gaussian estimates are provided in the Panel A and those based on Student-t($\bar{\eta}$) errors are displayed in Panels B through L for different degrees of freedom, $\bar{\eta}$. Reported confidence sets have a joint significance level of 5% over cross-sectional coefficients on each regressor.

Obtained against CAPM benchmark, Gaussian results in the Table 3.6 provide evidence of a positive alpha for most CBMFs in the sub-period following the 2011 Tohoku earthquake. In particular, all funds except one have strictly positive confidence sets estimated for their intercepts in the second sub-period. The same result obtains for CAPM intercepts in the Student-t case and is robust across various degrees of freedom. QCAPM and Fama-French estimates further reinforce this finding. Specifically, set estimates for QCAPM intercepts reported in the Table 3.7, albeit wider than their CAPM counterparts, comprise of only positive values in all but a few cases after March 2011. This occurs both in Gaussian and Student-t settings. Likewise, Fama-French results reported in the Table 3.8 also indicate strictly positive confidence sets for all but one intercept in the second sub-period suggesting a positive alpha on most CBMFs.

In terms of the risk sensitivity, main results on CBMFs are as follows. Reported in the Table 3.6, set estimates for market betas on the CAPM factor include zero and some negative and positive values. The inclusion of positive beta values could indicate possible exposure to the systematic market risk. However, although the upper bounds on set estimates are somewhat higher in the 1st sub-period covering the 2007-08 financial crisis, for all betas the estimated confidence sets overall cluster fairly tightly around zero. This is the case both under Normal and Student-t errors and occurs in both sub-periods. Thus, the CAPM-based analysis suggests that, even if the market betas on CBMFs are given by positive, upper set bounds, the sensitivity of CBMFs to the systematic market risk tends to be modest, even during the times of a considerable financial stress. This is similar to the finding of economically small loadings on financial benchmarks of Cummins and Weiss (2009) for CBMFs before mid-2008.

The estimation with an expanded set of factors yields similar results on the risk sensitivity of CBMFs. To that end, the QCAPM analysis also provides set estimates for market betas that, albeit tend to be somewhat wider than their CAPM analogs, also bunch up closely around zero with the positive upper bound that is quite small. The sensitivity of CBMFs to the coskewness risk is also fairly muted given rather narrow confidence intervals that cover zero and surrounding values estimated for coskewness betas. Overall, CBMFs could be relatively more sensitive to the coskewness risk than the traditional market risk given mostly wider confidence sets for coskewness betas as compared to their market beta equivalents. Taken together, QCAPM estimates suggest at most a moderate sensitivity of CBMFs vis-a-vis financial benchmarks even if true betas on each QCAPM factor are equal to the largest positive value in their respective confidence sets.

The analysis against the Fama-French benchmark provides further evidence of a rather muted exposure of CBMFs to fluctuations in financial benchmarks. In particular, Fama-French set estimates for betas on each risk factor tend to be fairly closely distributed around zero. For market betas, estimated confidence intervals have somewhat smaller lower bounds and are overall similar to their CAPM counterparts. Results indicate a potentially important role for the SMB factor during the 1st period covering the 2007-08 financial crisis. For that period, the SMB portfolio has the most dispersed confidence sets for its cross-sectional betas among the three Fama-French factors. After March 2011, these become more conservative and resemble fairly narrow beta intervals that enclose zero estimated for the HML factor. Overall, given small positive upper set bounds for loadings on each Fama-French factor, the sensitivity of CBMFs to movements in financial benchmarks is likely to be moderate, even if all true factor betas are at their maximum values within the sets.

Notably, estimated confidence sets include zeros and some negative values for all betas on every risk factor in CAPM, QCAPM and Fama-French benchmarks. Beta estimates, thus, suggest that CBMFs could be zero-beta or even negative-beta investments and, as such, could pose a valuable addition to a larger investment portfolio due to their diversification potential.

3.6 Conclusion

This paper makes available a formal analysis of CBMFs assessing these funds jointly in terms of their risk sensitivity with respect to financial markets and the overall ability to produce a positive alpha. For this purpose, inference relies on exact, simultaneous confidence sets assembled respectively for cross-sectional intercepts and factor loadings in the MLR model. These sets are constructed using the method of Beaulieu, Dufour and Khalaf (2018) in a Gaussian setting based on the inverted Hotelling test. We also offer an extension of the latter method to the scenario with Student-t errors by proposing to substitute the Fisher-based cut-off point with the one obtained from the simulated pivotal null distribution of the Hotelling statistic. The extended method is applied to study CBMFs in the Student-t setting. The simultaneity and size accuracy of estimated confidence sets allows to examine the overall performance across CBMFs and facilitates a reliable inference in small samples.

CBMFs are assessed against the traditional single-factor CAPM benchmark as well as its multifactor extensions. In particular, we estimate the QCAPM specification, which augments the market return with a mimicking portfolio for its square to capture the coskewness risk. In addition, the analysis relies on the Fama-French benchmark with SMB and HML factors considered in conjunction with the traditional market return. The assessment proceeds in the context of a large-scale, exogenous catastrophic event, the 2011 Tohoku earthquake.

The analysis provides evidence of a positive alpha on CBMFs in the sub-period after the Tohoku earthquake. This result is robust across benchmarks and is observed in both Gaussian and Student-t settings. Empirical findings also suggest that the risk sensitivity of CBMFs with respect to financial markets is likely to be modest. Our results indicate that even if the factor betas are given by the largest positive values in the estimated confidence sets, the risk exposure of CBMFs is likely be at most moderate. Further, based on betas alone and without taking into account the information on the factor risk premiums, it is possible that CBMFs could be zero-beta or negative-beta assets given that zeros and negative values are also included in the estimated beta intervals.

Figure 3.1: Excess returns on CBMFs between 11/2004 − 12/2015 (Panel A)

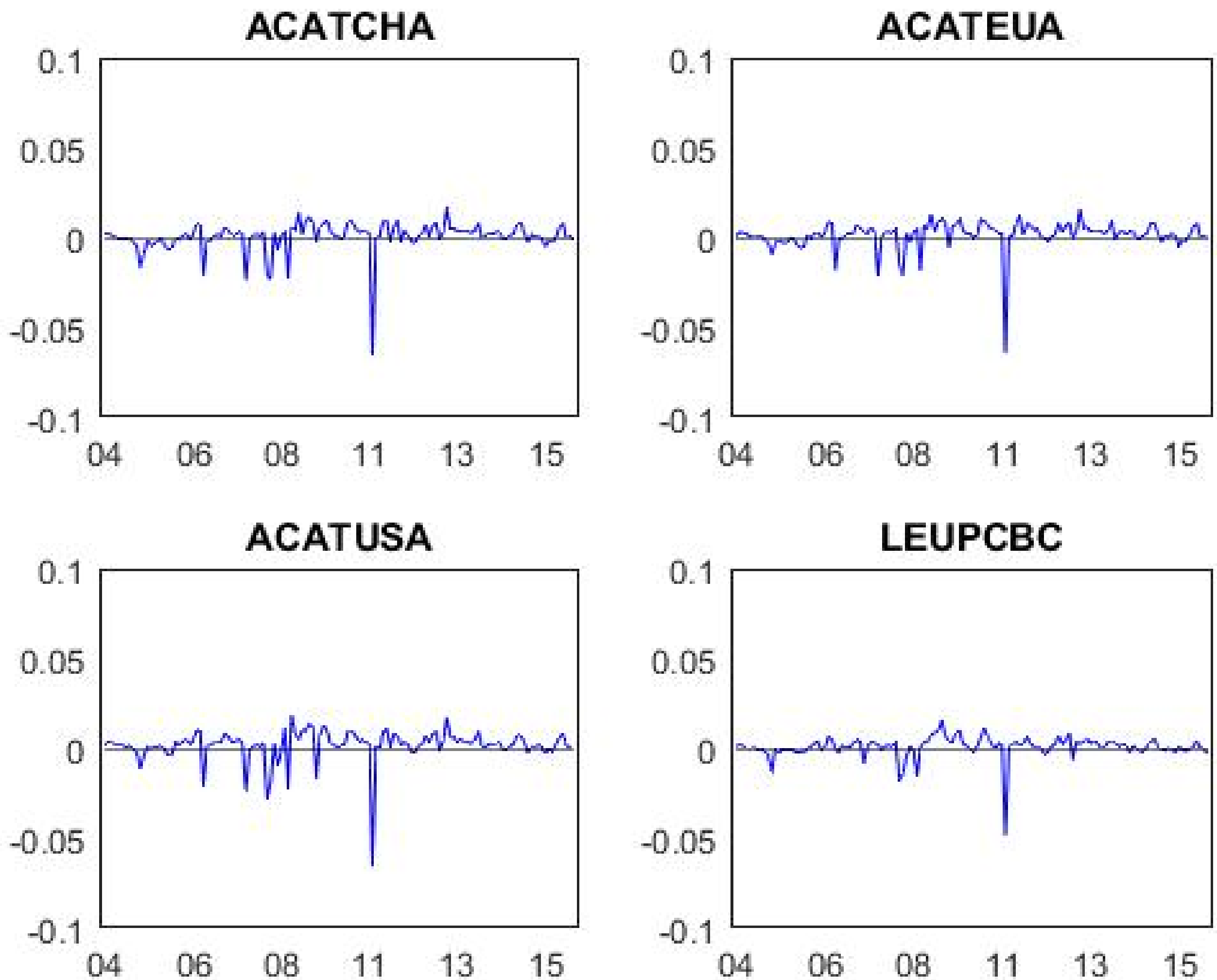
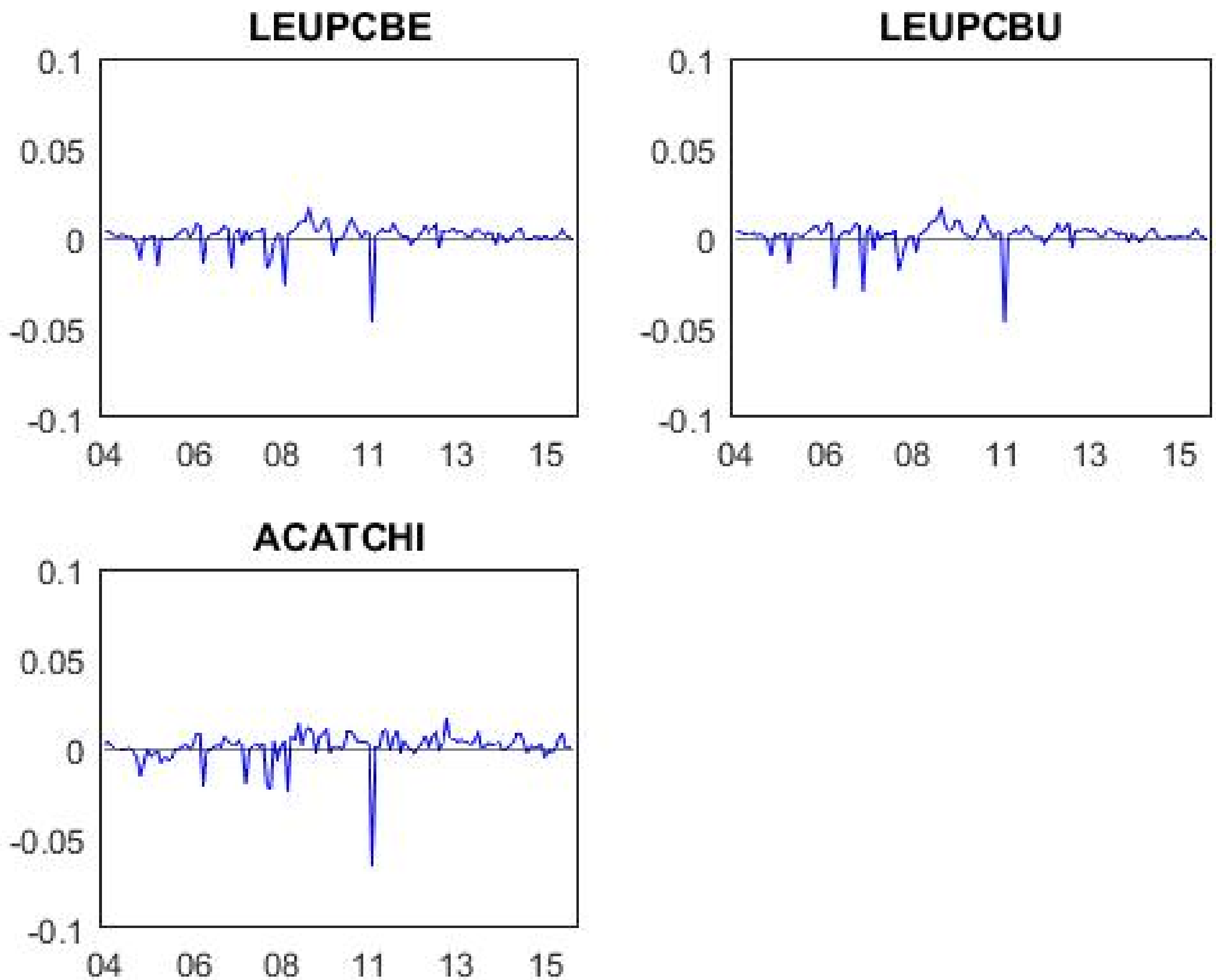


Figure 3.2: Excess returns on CBMFs between 11/2004 − 12/2015 (Panel B)



Tables

Table 3.1: Funds used in the analysis

#	Bloomberg Ticker	Fund Name
1	ACATCHA	Falcon Cat Bond Fund Class A CHF
2	ACATEUA	Falcon Cat Bond Fund Class A EUR
3	ACATUSA	Falcon Cat Bond Fund Class A USD
4	ACATCHI	Falcon Cat Bond Fund Class I CHF
5	LEUPCBC	LGT CH Cat Bond Fund (CHF) A
6	LEUPCBE	LGT CH Cat Bond Fund (EUR) A
7	LEUPCBU	LGT CH Cat Bond Fund (USD) A

Table 3.2: Gaussian test

#	Model	Period		
		11/2004 - 03/2011	04/2011 - 12/2015	11/2004 - 12/2015
1	CAPM	0.001	0.001	0.001
2	QCAPM	0.001	0.001	0.001
3	Fama-French	0.001	0.001	0.001

Note: Reported estimates are p-values for the Combined Goodness-of-Fit (CGF) test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013). The test is defined for the joint null hypothesis of skewness and kurtosis in the error distribution coinciding with those for the Gaussian case.

Table 3.3: Student-t test

#	Model	Period		
		11/2004 - 03/2011	04/2011 - 12/2015	11/2004 - 12/2015
1	CAPM	[2]	[2, 6]	[2]
2	QCAPM	[2]	[2, 6]	[2]
3	Fama-French	[2]	[2, 6]	[2]

Note: Reported intervals are exact confidence sets (CS) estimated for the degrees of freedom parameter, η, from the *i.i.d.* jointly multivariate Student-t(η) error distribution. Estimated CS contain only values of η for which the joint null hypothesis, that imposes Student-t($\bar{\eta}$) values of skewness and kurtosis, is not rejected. Assessment of the latter null hypothesis relies on p-values for the CGF test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013). Specifically, a given value of η is retained in the 5%-level CS only if the associated p-value exceeds 5%.

Table 3.4: Descriptive statistics

#	**Var**	**11/2004 - 03/2011**				**04/2011 - 12/2015**				**11/2004 - 12/2015**			
		Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt
1	acatcha	-0.001	0.011	-3.43	19.81	0.002	0.004	0.77	3.65	0.000	0.009	-3.97	28.45
2	acateua	0.000	0.010	-3.89	24.15	0.003	0.004	0.81	3.95	0.001	0.008	-4.51	34.97
3	acateusa	0.001	0.011	-3.15	17.18	0.003	0.004	1.00	4.48	0.002	0.009	-3.81	26.17
4	leupcbc	0.000	0.008	-3.40	21.43	0.001	0.003	-0.02	3.06	0.001	0.006	-4.05	31.96
5	leupcbe	0.000	0.009	-2.71	13.68	0.002	0.003	-0.11	3.22	0.001	0.007	-3.37	21.32
6	leupcbu	0.001	0.009	-2.90	13.77	0.002	0.003	-0.05	3.40	0.001	0.007	-3.62	21.89
7	acatchi	-0.001	0.010	-3.38	19.60	0.003	0.004	0.82	3.72	0.001	0.009	-3.91	28.07
8	Mkt	0.004	0.049	-0.90	4.92	0.008	0.035	-0.03	3.76	0.006	0.044	-0.77	5.24
9	Mkt2	0.006	0.032	-0.99	4.41	0.010	0.021	-0.49	3.90	0.008	0.028	-1.03	5.13
10	SMB	0.002	0.026	0.94	5.20	-0.002	0.020	-0.13	2.28	0.000	0.023	0.74	5.05
11	HML	-0.001	0.039	1.57	10.44	-0.003	0.020	0.22	3.26	-0.002	0.032	1.64	13.02

Table 3.5: Descriptive statistics - correlations

11/2004 - 03/2011

Var	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	Mkt	Mkt2	SMB	HML
acatcha	1										
acateua	0.99	1									
acateusa	0.96	0.96	1								
leupcbc	0.82	0.81	0.77	1							
leupcbe	0.74	0.74	0.69	0.92	1						
leupcbu	0.75	0.75	0.73	0.85	0.93	1					
acatchi	0.99	0.98	0.95	0.82	0.74	0.75	1				
Mkt	0.17	0.15	0.18	0.36	0.36	0.32	0.16	1			
Mkt2	0.12	0.10	0.05	0.21	0.21	0.16	0.10	0.58	1		
SMB	0.05	0.05	0.08	0.11	0.10	0.11	0.04	0.45	-0.07	1	
HML	0.06	0.06	0.13	0.18	0.19	0.16	0.05	0.47	0.07	0.35	1

04/2011 - 12/2015

Var	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	Mkt	Mkt2	SMB	HML
acatcha	1										
acateua	0.96	1									
acateusa	0.96	0.98	1								
leupcbc	0.64	0.64	0.68	1							
leupcbe	0.62	0.63	0.67	0.99	1						
leupcbu	0.64	0.65	0.69	0.99	0.99	1					
acatchi	0.99	0.96	0.96	0.64	0.62	0.64	1				
Mkt	0.04	-0.03	-0.02	-0.06	-0.10	-0.06	0.04	1			
Mkt2	-0.05	-0.13	-0.14	-0.05	-0.10	-0.08	-0.07	0.34	1		
SMB	0.21	0.15	0.15	-0.01	-0.04	-0.01	0.22	0.36	0.04	1	
HML	0.21	0.16	0.16	0.03	0.01	0.03	0.22	0.30	-0.28	0.17	1

11/2004 - 12/2015

Var	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	Mkt	Mkt2	SMB	HML
acatcha	1										
acateua	0.99	1									
acateusa	0.96	0.96	1								
leupcbc	0.80	0.80	0.76	1							
leupcbe	0.73	0.73	0.69	0.93	1						
leupcbu	0.74	0.74	0.73	0.86	0.93	1					
acatchi	0.99	0.98	0.95	0.80	0.73	0.74	1				
Mkt	0.15	0.12	0.15	0.29	0.28	0.26	0.14	1			
Mkt2	0.10	0.07	0.04	0.18	0.17	0.13	0.09	0.52	1		
SMB	0.06	0.05	0.07	0.08	0.07	0.08	0.05	0.42	-0.04	1	
HML	0.07	0.07	0.13	0.16	0.17	0.14	0.07	0.43	-0.01	0.30	

Note: Sample moments estimated for CBMFs are reported in rows 1-7. Mkt, $Mkt2$ are respectively excess (net of the risk-free rate) market return and a return on a mimicking portfolio for its square. SMB, HML are excess returns (net of the risk-free rate) on Fama-French factors.

Table 3.6: CAPM

CBMFs	11/2004 - 03/2011		04/2011 - 08/2014	
	CS(a)	**CS(b_M)**	**CS(a)**	**CS(b_M)**
Panel A: Gaussian				
acatcha	(-0.00611 , 0.00359)	(-0.06210 , 0.13548)	**(0.00011 , 0.00480)***	(-0.05991 , 0.06988)
acateua	(-0.00463 , 0.00461)	(-0.06443 , 0.12390)	**(0.00092 , 0.00528)***	(-0.06414 , 0.05660)
acatusa	(-0.00476 , 0.00552)	(-0.06323 , 0.14646)	**(0.00103 , 0.00545)***	(-0.06315 , 0.05925)
leupcbc	(-0.00332 , 0.00340)	(-0.01117 , 0.12585)	(-0.00020 , 0.00295)	(-0.04805 , 0.03908)
leupcbe	(-0.00366 , 0.00395)	(-0.01420 , 0.14094)	**(0.00024 , 0.00342)***	(-0.05210 , 0.03605)
leupcbu	(-0.00334 , 0.00485)	(-0.02370 , 0.14328)	**(0.00050 , 0.00356)***	(-0.04719 , 0.03775)
acatchi	(-0.00587 , 0.00384)	(-0.06557 , 0.13241)	**(0.00056 , 0.00523)***	(-0.06057 , 0.06874)
Panel B: Student-t(1)				
acatcha	(-0.00567 , 0.00315)	(-0.07425 , 0.14763)	**(0.00030 , 0.00461)***	(-0.06380 , 0.07378)
acateua	(-0.00421 , 0.00419)	(-0.07602 , 0.13548)	**(0.00109 , 0.00510)***	(-0.06776 , 0.06023)
acatusa	(-0.00430 , 0.00506)	(-0.07613 , 0.15936)	**(0.00121 , 0.00528)***	(-0.06683 , 0.06292)
leupcbc	(-0.00301 , 0.00310)	(-0.01960 , 0.13428)	(-0.00007 , 0.00282)	(-0.05066 , 0.04169)
leupcbe	(-0.00332 , 0.00361)	(-0.02374 , 0.15048)	**(0.00036 , 0.00329)***	(-0.05475 , 0.03869)
leupcbu	(-0.00297 , 0.00448)	(-0.03397 , 0.15355)	**(0.00062 , 0.00344)***	(-0.04974 , 0.04030)
acatchi	(-0.00543 , 0.00340)	(-0.07774 , 0.14459)	**(0.00075 , 0.00505)***	(-0.06445 , 0.07262)
Panel C: Student-t(2)				
acatcha	(-0.00596 , 0.00344)	(-0.07034 , 0.14371)	**(0.00018 , 0.00473)***	(-0.05910 , 0.06908)
acateua	(-0.00449 , 0.00447)	(-0.07228 , 0.13175)	**(0.00098 , 0.00521)***	(-0.06339 , 0.05586)
acatusa	(-0.00461 , 0.00537)	(-0.07197 , 0.15520)	**(0.00110 , 0.00539)***	(-0.06240 , 0.05849)
leupcbc	(-0.00322 , 0.00330)	(-0.01688 , 0.13156)	(-0.00015 , 0.00290)	(-0.04751 , 0.03854)
leupcbe	(-0.00355 , 0.00384)	(-0.02066 , 0.14741)	**(0.00028 , 0.00337)***	(-0.05156 , 0.03550)
leupcbu	(-0.00322 , 0.00473)	(-0.03066 , 0.15024)	**(0.00054 , 0.00352)***	(-0.04667 , 0.03722)
acatchi	(-0.00573 , 0.00369)	(-0.07382 , 0.14066)	**(0.00063 , 0.00516)***	(-0.05977 , 0.06794)
Panel D: Student-t(3)				
acatcha	(-0.00605 , 0.00353)	(-0.06209 , 0.13546)	**(0.00012 , 0.00479)***	(-0.06037 , 0.07035)
acateua	(-0.00458 , 0.00455)	(-0.06442 , 0.12388)	**(0.00092 , 0.00527)***	(-0.06457 , 0.05703)
acatusa	(-0.00470 , 0.00546)	(-0.06321 , 0.14644)	**(0.00104 , 0.00545)***	(-0.06359 , 0.05968)
leupcbc	(-0.00328 , 0.00336)	(-0.01116 , 0.12584)	(-0.00019 , 0.00295)	(-0.04836 , 0.03939)
leupcbe	(-0.00362 , 0.00390)	(-0.01418 , 0.14093)	**(0.00024 , 0.00342)***	(-0.05242 , 0.03636)
leupcbu	(-0.00329 , 0.00480)	(-0.02369 , 0.14327)	**(0.00050 , 0.00356)***	(-0.04749 , 0.03805)
acatchi	(-0.00581 , 0.00378)	(-0.06555 , 0.13240)	**(0.00057 , 0.00523)***	(-0.06103 , 0.06920)
Panel E: Student-t(4)				
acatcha	(-0.00607 , 0.00355)	(-0.06182 , 0.13520)	**(0.00014 , 0.00477)***	(-0.05927 , 0.06925)
acateua	(-0.00459 , 0.00457)	(-0.06417 , 0.12363)	**(0.00095 , 0.00525)***	(-0.06355 , 0.05601)
acatusa	(-0.00472 , 0.00548)	(-0.06293 , 0.14617)	**(0.00106 , 0.00542)***	(-0.06256 , 0.05865)
leupcbc	(-0.00329 , 0.00338)	(-0.01098 , 0.12566)	(-0.00018 , 0.00293)	(-0.04762 , 0.03865)
leupcbe	(-0.00363 , 0.00392)	(-0.01398 , 0.14072)	**(0.00026 , 0.00340)***	(-0.05167 , 0.03562)
leupcbu	(-0.00331 , 0.00482)	(-0.02347 , 0.14305)	**(0.00052 , 0.00354)***	(-0.04678 , 0.03733)
acatchi	(-0.00583 , 0.00380)	(-0.06529 , 0.13213)	**(0.00059 , 0.00520)***	(-0.05994 , 0.06811)

Table 3.6 continued: CAPM

CBMFs	11/2004 - 03/2011		04/2011 - 08/2014	
	CS(a)	**CS(b_M)**	**CS(a)**	**CS(b_M)**
Panel F: Student-t(5)				
acatcha	(-0.00601 , 0.00349)	(-0.06020 , 0.13358)	**(0.00008 , 0.00483)***	(-0.06035 , 0.07033)
acateua	(-0.00454 , 0.00451)	(-0.06262 , 0.12209)	**(0.00089 , 0.00531)***	(-0.06455 , 0.05702)
acatusa	(-0.00466 , 0.00542)	(-0.06121 , 0.14444)	**(0.00100 , 0.00548)***	(-0.06357 , 0.05966)
leupcbc	(-0.00325 , 0.00334)	(-0.00985 , 0.12453)	(-0.00022 , 0.00297)	(-0.04835 , 0.03937)
leupcbe	(-0.00358 , 0.00387)	(-0.01271 , 0.13945)	**(0.00022 , 0.00344)***	(-0.05240 , 0.03635)
leupcbu	(-0.00326 , 0.00477)	(-0.02210 , 0.14167)	**(0.00047 , 0.00358)***	(-0.04748 , 0.03804)
acatchi	(-0.00577 , 0.00374)	(-0.06366 , 0.13051)	**(0.00053 , 0.00526)***	(-0.06101 , 0.06918)
Panel G: Student-t(6)				
acatcha	(-0.00601 , 0.00349)	(-0.06256 , 0.13593)	**(0.00009 , 0.00481)***	(-0.05920 , 0.06918)
acateua	(-0.00454 , 0.00451)	(-0.06487 , 0.12433)	**(0.00090 , 0.00529)***	(-0.06348 , 0.05595)
acatusa	(-0.00466 , 0.00542)	(-0.06371 , 0.14694)	**(0.00102 , 0.00547)***	(-0.06249 , 0.05858)
leupcbc	(-0.00325 , 0.00333)	(-0.01149 , 0.12617)	(-0.00021 , 0.00296)	(-0.04758 , 0.03860)
leupcbe	(-0.00358 , 0.00387)	(-0.01456 , 0.14130)	**(0.00023 , 0.00343)***	(-0.05163 , 0.03557)
leupcbu	(-0.00326 , 0.00477)	(-0.02409 , 0.14367)	**(0.00048 , 0.00357)***	(-0.04673 , 0.03729)
acatchi	(-0.00577 , 0.00374)	(-0.06602 , 0.13287)	**(0.00055 , 0.00525)***	(-0.05987 , 0.06804)
Panel H: Student-t(7)				
acatcha	(-0.00606 , 0.00354)	(-0.06228 , 0.13565)	**(0.00005 , 0.00486)***	(-0.06058 , 0.07056)
acateua	(-0.00459 , 0.00456)	(-0.06460 , 0.12407)	**(0.00086 , 0.00533)***	(-0.06476 , 0.05723)
acatusa	(-0.00471 , 0.00547)	(-0.06342 , 0.14665)	**(0.00097 , 0.00551)***	(-0.06379 , 0.05988)
leupcbc	(-0.00329 , 0.00337)	(-0.01129 , 0.12597)	(-0.00024 , 0.00299)	(-0.04850 , 0.03953)
leupcbe	(-0.00362 , 0.00391)	(-0.01434 , 0.14108)	**(0.00019 , 0.00346)***	(-0.05256 , 0.03650)
leupcbu	(-0.00330 , 0.00481)	(-0.02385 , 0.14343)	**(0.00045 , 0.00360)***	(-0.04763 , 0.03819)
acatchi	(-0.00583 , 0.00379)	(-0.06574 , 0.13259)	**(0.00050 , 0.00529)***	(-0.06124 , 0.06940)
Panel I: Student-t(8)				
acatcha	(-0.00608 , 0.00356)	(-0.06019 , 0.13357)	**(0.00005 , 0.00486)***	(-0.05933 , 0.06931)
acateua	(-0.00461 , 0.00458)	(-0.06261 , 0.12208)	**(0.00086 , 0.00533)***	(-0.06360 , 0.05607)
acatusa	(-0.00474 , 0.00549)	(-0.06120 , 0.14443)	**(0.00097 , 0.00551)***	(-0.06261 , 0.05871)
leupcbc	(-0.00330 , 0.00339)	(-0.00984 , 0.12453)	(-0.00024 , 0.00299)	(-0.04766 , 0.03869)
leupcbe	(-0.00364 , 0.00393)	(-0.01270 , 0.13944)	**(0.00020 , 0.00346)***	(-0.05171 , 0.03566)
leupcbu	(-0.00332 , 0.00483)	(-0.02209 , 0.14167)	**(0.00046 , 0.00360)***	(-0.04682 , 0.03737)
acatchi	(-0.00585 , 0.00381)	(-0.06365 , 0.13050)	**(0.00050 , 0.00529)***	(-0.06000 , 0.06817)
Panel J: Student-t(9)				
acatcha	(-0.00595 , 0.00343)	(-0.06191 , 0.13529)	**(0.00008 , 0.00483)***	(-0.05988 , 0.06986)
acateua	(-0.00448 , 0.00446)	(-0.06425 , 0.12371)	**(0.00089 , 0.00531)***	(-0.06412 , 0.05658)
acatusa	(-0.00460 , 0.00535)	(-0.06303 , 0.14626)	**(0.00100 , 0.00548)***	(-0.06313 , 0.05923)
leupcbc	(-0.00321 , 0.00329)	(-0.01104 , 0.12572)	(-0.00022 , 0.00297)	(-0.04803 , 0.03906)
leupcbe	(-0.00354 , 0.00382)	(-0.01405 , 0.14079)	**(0.00022 , 0.00344)***	(-0.05209 , 0.03603)
leupcbu	(-0.00321 , 0.00472)	(-0.02354 , 0.14312)	**(0.00047 , 0.00358)***	(-0.04718 , 0.03773)
acatchi	(-0.00571 , 0.00368)	(-0.06538 , 0.13222)	**(0.00053 , 0.00526)***	(-0.06055 , 0.06872)

Table 3.6 continued: CAPM

CBMFs	**11/2004 - 03/2011**		**04/2011 - 08/2014**	
	CS(a)	**CS($\mathbf{b_M}$)**	**CS(a)**	**CS($\mathbf{b_M}$)**
Panel K: Student-t(10)				
acatcha	(-0.00604 , 0.00352)	(-0.06016 , 0.13354)	**(0.00008 , 0.00483)***	(-0.06004 , 0.07002)
acateua	(-0.00457 , 0.00455)	(-0.06259 , 0.12205)	**(0.00089 , 0.00530)***	(-0.06426 , 0.05673)
acatusa	(-0.00470 , 0.00546)	(-0.06117 , 0.14440)	**(0.00100 , 0.00548)***	(-0.06328 , 0.05938)
leupcbc	(-0.00327 , 0.00336)	(-0.00982 , 0.12450)	(-0.00022 , 0.00297)	(-0.04814 , 0.03917)
leupcbe	(-0.00361 , 0.00390)	(-0.01267 , 0.13942)	**(0.00022 , 0.00344)***	(-0.05220 , 0.03614)
leupcbu	(-0.00329 , 0.00480)	(-0.02206 , 0.14164)	**(0.00048 , 0.00358)***	(-0.04728 , 0.03784)
acatchi	(-0.00581 , 0.00378)	(-0.06362 , 0.13047)	**(0.00053 , 0.00526)***	(-0.06071 , 0.06887)
Panel L: Student-t(50)				
acatcha	(-0.00610 , 0.00358)	(-0.05923 , 0.13261)	**(0.00005 , 0.00486)***	(-0.05944 , 0.06941)
acateua	(-0.00462 , 0.00460)	(-0.06170 , 0.12116)	**(0.00086 , 0.00534)***	(-0.06370 , 0.05616)
acatusa	(-0.00475 , 0.00551)	(-0.06018 , 0.14341)	**(0.00097 , 0.00551)***	(-0.06271 , 0.05880)
leupcbc	(-0.00331 , 0.00340)	(-0.00918 , 0.12386)	(-0.00024 , 0.00299)	(-0.04773 , 0.03876)
leupcbe	(-0.00365 , 0.00394)	(-0.01194 , 0.13869)	**(0.00019 , 0.00346)***	(-0.05178 , 0.03573)
leupcbu	(-0.00333 , 0.00484)	(-0.02128 , 0.14086)	**(0.00045 , 0.00360)***	(-0.04688 , 0.03744)
acatchi	(-0.00586 , 0.00383)	(-0.06269 , 0.12954)	**(0.00050 , 0.00530)***	(-0.06010 , 0.06827)

Note: $CS(a)$ and $CS(b_M)$ are exact, simultaneous confidence sets estimated for respectively intercepts and loadings on the excess market return in the CAPM-based model. Panel A displays results obtained under Gaussian errors. Panels B-L contain estimates from the model with Student-t(η) errors under varying degrees of freedom, η.

* marks CS without zero. The significance level of all estimated CS is 5%.

Table 3.7: QCAPM

CBMF	11/2004 - 03/2011			04/2011 - 08/2014		
	CS(a)	**CS**($\mathbf{b_M}$)	**CS**($\mathbf{b_S}$)	**CS(a)**	**CS**($\mathbf{b_M}$)	**CS**($\mathbf{b_S}$)
Panel A: Gaussian						
acatcha	(-0.00625 , 0.00366)	(-0.08872 , 0.15594)	(-0.17914 , 0.19535)	**(0.00001 , 0.00515)***	(-0.06168 , 0.07768)	(-0.13301 , 0.10321)
acateua	(-0.00475 , 0.00468)	(-0.08889 , 0.14435)	(-0.17323 , 0.18377)	**(0.00092 , 0.00568)***	(-0.06341 , 0.06556)	(-0.13326 , 0.08536)
acatusa	(-0.00475 , 0.00574)	(-0.07753 , 0.18162)	(-0.22581 , 0.17088)	**(0.00107 , 0.00588)***	(-0.06173 , 0.06877)	(-0.13770 , 0.08351)
leupcbc	(-0.00339 , 0.00348)	(-0.02768 , 0.14202)	(-0.12944 , 0.13032)	(-0.00031 , 0.00314)	(-0.05046 , 0.04328)	(-0.08386 , 0.07502)
leupcbe	(-0.00375 , 0.00402)	(-0.03336 , 0.15879)	(-0.14532 , 0.14879)	**(0.00016 , 0.00365)***	(-0.05347 , 0.04121)	(-0.08963 , 0.07086)
leupcbu	(-0.00338 , 0.00498)	(-0.03967 , 0.16705)	(-0.16848 , 0.14794)	**(0.00041 , 0.00378)***	(-0.04874 , 0.04254)	(-0.08537 , 0.06934)
acatchi	(-0.00601 , 0.00391)	(-0.09185 , 0.15331)	(-0.18054 , 0.19472)	**(0.00051 , 0.00562)***	(-0.06132 , 0.07727)	(-0.13672 , 0.09820)
Panel B: Student-t(1)						
acatcha	(-0.00591 , 0.00332)	(-0.11820 , 0.18542)	(-0.22145 , 0.23765)	**(0.00010 , 0.00507)***	(-0.06500 , 0.08101)	(-0.13586 , 0.10606)
acateua	(-0.00443 , 0.00436)	(-0.11699 , 0.17245)	(-0.21356 , 0.22410)	**(0.00100 , 0.00560)***	(-0.06649 , 0.06864)	(-0.13590 , 0.08800)
acatusa	(-0.00439 , 0.00539)	(-0.10876 , 0.21286)	(-0.27062 , 0.21568)	**(0.00114 , 0.00580)***	(-0.06484 , 0.07189)	(-0.14037 , 0.08618)
leupcbc	(-0.00316 , 0.00324)	(-0.04813 , 0.16247)	(-0.15878 , 0.15966)	(-0.00026 , 0.00309)	(-0.05270 , 0.04551)	(-0.08578 , 0.07694)
leupcbe	(-0.00349 , 0.00376)	(-0.05651 , 0.18194)	(-0.17854 , 0.18201)	**(0.00022 , 0.00360)***	(-0.05573 , 0.04347)	(-0.09157 , 0.07280)
leupcbu	(-0.00310 , 0.00470)	(-0.06458 , 0.19196)	(-0.20422 , 0.18368)	**(0.00047 , 0.00372)***	(-0.05092 , 0.04472)	(-0.08724 , 0.07121)
acatchi	(-0.00567 , 0.00358)	(-0.12140 , 0.18286)	(-0.22293 , 0.23711)	**(0.00059 , 0.00553)***	(-0.06463 , 0.08058)	(-0.13956 , 0.10104)
Panel C: Student-t(2)						
acatcha	(-0.00611 , 0.00352)	(-0.09884 , 0.16606)	(-0.19533 , 0.21153)	**(0.00001 , 0.00515)***	(-0.06478 , 0.08078)	(-0.13194 , 0.10214)
acateua	(-0.00463 , 0.00455)	(-0.09853 , 0.15400)	(-0.18866 , 0.19920)	**(0.00092 , 0.00568)***	(-0.06628 , 0.06843)	(-0.13227 , 0.08437)
acatusa	(-0.00460 , 0.00560)	(-0.08825 , 0.19235)	(-0.24295 , 0.18802)	**(0.00107 , 0.00588)***	(-0.06463 , 0.07168)	(-0.13670 , 0.08250)
leupcbc	(-0.00330 , 0.00338)	(-0.03470 , 0.14905)	(-0.14066 , 0.14154)	(-0.00031 , 0.00314)	(-0.05255 , 0.04536)	(-0.08314 , 0.07430)
leupcbe	(-0.00365 , 0.00392)	(-0.04131 , 0.16673)	(-0.15803 , 0.16149)	**(0.00016 , 0.00365)***	(-0.05558 , 0.04332)	(-0.08890 , 0.07013)
leupcbu	(-0.00327 , 0.00487)	(-0.04822 , 0.17560)	(-0.18215 , 0.16161)	**(0.00041 , 0.00378)***	(-0.05077 , 0.04457)	(-0.08467 , 0.06864)
acatchi	(-0.00587 , 0.00378)	(-0.10200 , 0.16346)	(-0.19676 , 0.21094)	**(0.00051 , 0.00561)***	(-0.06441 , 0.08036)	(-0.13566 , 0.09714)

Table 3.7 continued: QCAPM

CBMFs	11/2004 - 03/2011			04/2011 - 08/2014		
	CS(a)	**CS($\mathbf{b_M}$)**	**CS($\mathbf{b_S}$)**	**CS(a)**	**CS($\mathbf{b_M}$)**	**CS($\mathbf{b_S}$)**
Panel D: Student-t(3)						
acatcha	(-0.00610 , 0.00351)	(-0.09179 , 0.15901)	(-0.18863 , 0.20483)	**(0.00006 , 0.00510)***	(-0.06551 , 0.08151)	(-0.13057 , 0.10077)
acateua	(-0.00461 , 0.00454)	(-0.09181 , 0.14727)	(-0.18228 , 0.19281)	**(0.00096 , 0.00564)***	(-0.06696 , 0.06911)	(-0.13101 , 0.08310)
acatusa	(-0.00459 , 0.00558)	(-0.08079 , 0.18488)	(-0.23586 , 0.18093)	**(0.00111 , 0.00584)***	(-0.06532 , 0.07236)	(-0.13542 , 0.08123)
leupcbc	(-0.00329 , 0.00337)	(-0.02981 , 0.14416)	(-0.13602 , 0.13690)	(-0.00028 , 0.00311)	(-0.05304 , 0.04586)	(-0.08223 , 0.07339)
leupcbe	(-0.00363 , 0.00391)	(-0.03577 , 0.16120)	(-0.15277 , 0.15624)	**(0.00019 , 0.00362)***	(-0.05608 , 0.04381)	(-0.08797 , 0.06920)
leupcbu	(-0.00326 , 0.00485)	(-0.04226 , 0.16964)	(-0.17650 , 0.15595)	**(0.00044 , 0.00375)***	(-0.05125 , 0.04505)	(-0.08378 , 0.06775)
acatchi	(-0.00586 , 0.00376)	(-0.09493 , 0.15639)	(-0.19005 , 0.20423)	**(0.00055 , 0.00557)***	(-0.06514 , 0.08108)	(-0.13430 , 0.09578)
Panel E: Student-t(4)						
acatcha	(-0.00617 , 0.00358)	(-0.09059 , 0.15781)	(-0.18049 , 0.19669)	(-0.000001 , 0.00516)	(-0.06363 , 0.07963)	(-0.13115 , 0.10134)
acateua	(-0.00468 , 0.00461)	(-0.09067 , 0.14613)	(-0.17451 , 0.18505)	**(0.00091 , 0.00569)***	(-0.06522 , 0.06737)	(-0.13154 , 0.08363)
acatusa	(-0.00467 , 0.00566)	(-0.07952 , 0.18361)	(-0.22723 , 0.17230)	**(0.00105 , 0.00589)***	(-0.06355 , 0.07060)	(-0.13595 , 0.08176)
leupcbc	(-0.00334 , 0.00342)	(-0.02898 , 0.14333)	(-0.13037 , 0.13125)	(-0.00032 , 0.00315)	(-0.05177 , 0.04459)	(-0.08261 , 0.07377)
leupcbe	(-0.00369 , 0.00397)	(-0.03483 , 0.16026)	(-0.14637 , 0.14984)	**(0.00015 , 0.00366)***	(-0.05480 , 0.04253)	(-0.08836 , 0.06959)
leupcbu	(-0.00332 , 0.00492)	(-0.04125 , 0.16863)	(-0.16961 , 0.14907)	**(0.00041 , 0.00379)***	(-0.05002 , 0.04381)	(-0.08415 , 0.06812)
acatchi	(-0.00593 , 0.00384)	(-0.09373 , 0.15519)	(-0.18189 , 0.19607)	**(0.00049 , 0.00563)***	(-0.06326 , 0.07921)	(-0.13487 , 0.09635)
Panel F: Student-t(5)						
acatcha	(-0.00616 , 0.00357)	(-0.09055 , 0.15777)	(-0.18486 , 0.20106)	**(0.00008 , 0.00508)***	(-0.06308 , 0.07908)	(-0.13002 , 0.10021)
acateua	(-0.00468 , 0.00461)	(-0.09063 , 0.14609)	(-0.17868 , 0.18921)	**(0.00099 , 0.00561)***	(-0.06471 , 0.06686)	(-0.13049 , 0.08259)
acatusa	(-0.00466 , 0.00566)	(-0.07947 , 0.18356)	(-0.23186 , 0.17693)	**(0.00113 , 0.00581)***	(-0.06304 , 0.07009)	(-0.13490 , 0.08070)
leupcbc	(-0.00334 , 0.00342)	(-0.02895 , 0.14329)	(-0.13340 , 0.13428)	(-0.00027 , 0.00309)	(-0.05140 , 0.04422)	(-0.08185 , 0.07301)
leupcbe	(-0.00369 , 0.00396)	(-0.03479 , 0.16022)	(-0.14981 , 0.15327)	**(0.00021 , 0.00361)***	(-0.05442 , 0.04216)	(-0.08759 , 0.06882)
leupcbu	(-0.00332 , 0.00491)	(-0.04121 , 0.16860)	(-0.17331 , 0.15276)	**(0.00046 , 0.00373)***	(-0.04966 , 0.04345)	(-0.08341 , 0.06738)
acatchi	(-0.00593 , 0.00383)	(-0.09369 , 0.15515)	(-0.18627 , 0.20045)	**(0.00058 , 0.00554)***	(-0.06272 , 0.07867)	(-0.13374 , 0.09523)

Table 3.7 continued: QCAPM

CBMFs	**11/2004 - 03/2011**			**04/2011 - 08/2014**		
	CS(a)	**CS(b_M)**	**CS(b_S)**	**CS(a)**	**CS(b_M)**	**CS(b_S)**
Panel G: Student-t(6)						
acatcha	(-0.00618 , 0.00359)	(-0.08846 , 0.15568)	(-0.18191 , 0.19811)	**(0.00003 , 0.00513)***	(-0.06302 , 0.07902)	(-0.12844 , 0.09864)
acateua	(-0.00469 , 0.00462)	(-0.08864 , 0.14410)	(-0.17587 , 0.18641)	**(0.00094 , 0.00566)***	(-0.06466 , 0.06681)	(-0.12904 , 0.08113)
acatusa	(-0.00468 , 0.00567)	(-0.07726 , 0.18135)	(-0.22874 , 0.17381)	**(0.00109 , 0.00586)***	(-0.06299 , 0.07003)	(-0.13342 , 0.07923)
leupcbc	(-0.00335 , 0.00343)	(-0.02750 , 0.14184)	(-0.13136 , 0.13224)	(-0.00030 , 0.00313)	(-0.05137 , 0.04418)	(-0.08079 , 0.07195)
leupcbe	(-0.00370 , 0.00397)	(-0.03315 , 0.15858)	(-0.14749 , 0.15096)	**(0.00018 , 0.00364)***	(-0.05439 , 0.04212)	(-0.08653 , 0.06776)
leupcbu	(-0.00333 , 0.00493)	(-0.03945 , 0.16683)	(-0.17082 , 0.15027)	**(0.00043 , 0.00376)***	(-0.04962 , 0.04342)	(-0.08238 , 0.06635)
acatchi	(-0.00594 , 0.00385)	(-0.09159 , 0.15305)	(-0.18332 , 0.19750)	**(0.00053 , 0.00559)***	(-0.06266 , 0.07861)	(-0.13218 , 0.09366)
Panel H: Student-t(7)						
acatcha	(-0.00616 , 0.00357)	(-0.09137 , 0.15859)	(-0.18103 , 0.19724)	**(0.00003 , 0.00513)***	(-0.06296 , 0.07896)	(-0.13292 , 0.10312)
acateua	(-0.00467 , 0.00460)	(-0.09141 , 0.14687)	(-0.17503 , 0.18557)	**(0.00094 , 0.00566)***	(-0.06460 , 0.06675)	(-0.13318 , 0.08528)
acatusa	(-0.00466 , 0.00565)	(-0.08034 , 0.18443)	(-0.22781 , 0.17288)	**(0.00108 , 0.00586)***	(-0.06293 , 0.06998)	(-0.13762 , 0.08342)
leupcbc	(-0.00333 , 0.00342)	(-0.02952 , 0.14386)	(-0.13075 , 0.13163)	(-0.00030 , 0.00313)	(-0.05133 , 0.04414)	(-0.08381 , 0.07497)
leupcbe	(-0.00369 , 0.00396)	(-0.03544 , 0.16087)	(-0.14681 , 0.15027)	**(0.00017 , 0.00364)***	(-0.05434 , 0.04208)	(-0.08957 , 0.07080)
leupcbu	(-0.00331 , 0.00491)	(-0.04191 , 0.16929)	(-0.17008 , 0.14953)	**(0.00043 , 0.00377)***	(-0.04958 , 0.04338)	(-0.08532 , 0.06929)
acatchi	(-0.00592 , 0.00383)	(-0.09451 , 0.15597)	(-0.18244 , 0.19662)	**(0.00052 , 0.00560)***	(-0.06260 , 0.07855)	(-0.13663 , 0.09812)
Panel I: Student-t(8)						
acatcha	(-0.00619 , 0.00360)	(-0.09069 , 0.15791)	(-0.17768 , 0.19389)	**(0.00003 , 0.00513)***	(-0.06352 , 0.07952)	(-0.13004 , 0.10023)
acateua	(-0.00470 , 0.00463)	(-0.09076 , 0.14622)	(-0.17184 , 0.18238)	**(0.00094 , 0.00566)***	(-0.06512 , 0.06727)	(-0.13051 , 0.08261)
acatusa	(-0.00469 , 0.00568)	(-0.07962 , 0.18371)	(-0.22426 , 0.16933)	**(0.00108 , 0.00586)***	(-0.06346 , 0.07050)	(-0.13492 , 0.08072)
leupcbc	(-0.00335 , 0.00344)	(-0.02904 , 0.14339)	(-0.12843 , 0.12931)	(-0.00030 , 0.00313)	(-0.05170 , 0.04452)	(-0.08187 , 0.07303)
leupcbe	(-0.00371 , 0.00398)	(-0.03490 , 0.16033)	(-0.14417 , 0.14764)	**(0.00017 , 0.00364)***	(-0.05473 , 0.04246)	(-0.08761 , 0.06884)
leupcbu	(-0.00334 , 0.00494)	(-0.04133 , 0.16871)	(-0.16725 , 0.14670)	**(0.00042 , 0.00377)***	(-0.04995 , 0.04375)	(-0.08343 , 0.06740)
acatchi	(-0.00595 , 0.00386)	(-0.09382 , 0.15529)	(-0.17908 , 0.19326)	**(0.00052 , 0.00560)***	(-0.06316 , 0.07911)	(-0.13377 , 0.09525)

Table 3.7 continued: QCAPM

CBMFs	**11/2004 - 03/2011**			**04/2011 - 08/2014**		
	CS(a)	**CS($\mathbf{b_M}$)**	**CS($\mathbf{b_S}$)**	**CS(a)**	**CS($\mathbf{b_M}$)**	**CS($\mathbf{b_S}$)**
Panel J: Student-t(9)						
acatcha	(-0.00608 , 0.00349)	(-0.09094 , 0.15816)	(-0.17986 , 0.19606)	**(0.00004 , 0.00512)***	(-0.06333 , 0.07933)	(-0.13051 , 0.10071)
acateua	(-0.00460 , 0.00453)	(-0.09101 , 0.14647)	(-0.17391 , 0.18445)	**(0.00095 , 0.00565)***	(-0.06494 , 0.06709)	(-0.13095 , 0.08305)
acatusa	(-0.00457 , 0.00557)	(-0.07989 , 0.18398)	(-0.22656 , 0.17163)	**(0.00109 , 0.00585)***	(-0.06327 , 0.07032)	(-0.13536 , 0.08117)
leupcbc	(-0.00328 , 0.00336)	(-0.02922 , 0.14357)	(-0.12993 , 0.13081)	(-0.00030 , 0.00312)	(-0.05157 , 0.04439)	(-0.08218 , 0.07335)
leupcbe	(-0.00362 , 0.00390)	(-0.03510 , 0.16053)	(-0.14588 , 0.14935)	**(0.00018 , 0.00364)***	(-0.05459 , 0.04233)	(-0.08793 , 0.06916)
leupcbu	(-0.00325 , 0.00484)	(-0.04155 , 0.16893)	(-0.16908 , 0.14854)	**(0.00043 , 0.00376)***	(-0.04982 , 0.04362)	(-0.08374 , 0.06771)
acatchi	(-0.00585 , 0.00375)	(-0.09408 , 0.15554)	(-0.18126 , 0.19544)	**(0.00053 , 0.00559)***	(-0.06296 , 0.07891)	(-0.13424 , 0.09572)
Panel K: Student-t(10)						
acatcha	(-0.00613 , 0.00354)	(-0.08792 , 0.15515)	(-0.17753 , 0.19374)	**(0.00003 , 0.00514)***	(-0.06249 , 0.07850)	(-0.12849 , 0.09869)
acateua	(-0.00464 , 0.00457)	(-0.08813 , 0.14359)	(-0.17170 , 0.18224)	**(0.00093 , 0.00567)***	(-0.06417 , 0.06632)	(-0.12908 , 0.08117)
acatusa	(-0.00462 , 0.00562)	(-0.07669 , 0.18078)	(-0.22410 , 0.16917)	**(0.00108 , 0.00587)***	(-0.06249 , 0.06954)	(-0.13347 , 0.07927)
leupcbc	(-0.00331 , 0.00339)	(-0.02713 , 0.14147)	(-0.12832 , 0.12920)	(-0.00031 , 0.00313)	(-0.05101 , 0.04383)	(-0.08082 , 0.07198)
leupcbe	(-0.00366 , 0.00393)	(-0.03273 , 0.15816)	(-0.14406 , 0.14752)	**(0.00017 , 0.00365)***	(-0.05403 , 0.04176)	(-0.08656 , 0.06779)
leupcbu	(-0.00328 , 0.00488)	(-0.03900 , 0.16638)	(-0.16712 , 0.14657)	**(0.00042 , 0.00377)***	(-0.04927 , 0.04307)	(-0.08241 , 0.06638)
acatchi	(-0.00589 , 0.00379)	(-0.09106 , 0.15252)	(-0.17893 , 0.19311)	**(0.00052 , 0.00560)***	(-0.06213 , 0.07808)	(-0.13222 , 0.09371)
Panel L: Student-t(50)						
acatcha	(-0.00619 , 0.00360)	(-0.08494 , 0.15216)	(-0.17483 , 0.19103)	**(0.000005 , 0.00516)***	(-0.06247 , 0.07847)	(-0.13182 , 0.10202)
acateua	(-0.00470 , 0.00463)	(-0.08529 , 0.14075)	(-0.16912 , 0.17966)	**(0.00092 , 0.00568)***	(-0.06415 , 0.06630)	(-0.13216 , 0.08426)
acatusa	(-0.00469 , 0.00569)	(-0.07353 , 0.17763)	(-0.22124 , 0.16630)	**(0.00106 , 0.00588)***	(-0.06247 , 0.06952)	(-0.13659 , 0.08239)
leupcbc	(-0.00336 , 0.00344)	(-0.02506 , 0.13941)	(-0.12645 , 0.12733)	(-0.00032 , 0.00315)	(-0.05100 , 0.04381)	(-0.08306 , 0.07422)
leupcbe	(-0.00371 , 0.00398)	(-0.03039 , 0.15582)	(-0.14193 , 0.14540)	**(0.00016 , 0.00366)***	(-0.05401 , 0.04175)	(-0.08882 , 0.07005)
leupcbu	(-0.00334 , 0.00494)	(-0.03648 , 0.16386)	(-0.16483 , 0.14429)	**(0.00041 , 0.00378)***	(-0.04926 , 0.04306)	(-0.08460 , 0.06856)
acatchi	(-0.00596 , 0.00386)	(-0.08807 , 0.14953)	(-0.17622 , 0.19040)	**(0.00050 , 0.00562)***	(-0.06211 , 0.07806)	(-0.13554 , 0.09702)

Note: $CS(a)$, $CS(b_M)$ and $CS(b_S)$ are exact, simultaneous confidence sets estimated for respectively intercepts, loadings on the excess market return and the mimicking portfolio for its square from the QCAPM-based model. Panel A displays results obtained under Gaussian errors. Panels B-L contain estimates from the model with Student-t(η) errors under varying degrees of freedom, η.

* marks CS without zero. The significance level of all estimated CS is 5%.

Table 3.8: Fama-French

CBMFs	11/2004 - 03/2011				04/2011 - 08/2014			
	CS(a)	CS(b_M)	CS(b_{SMB})	CS(b_{HML})	CS(a)	CS(b_M)	CS(b_{SMB})	CS(b_{HML})
Panel A: Gaussian								
acatcha	(-0.0062 , 0.0037)	(-0.0795 , 0.1629)	(-0.2306 , 0.2050)	(-0.1499 , 0.1392)	**(0.0004 , 0.0052)***	(-0.0816 , 0.0599)	(-0.0799 , 0.1646)	(-0.0752 , 0.1595)
acateua	(-0.0047 , 0.0047)	(-0.0834 , 0.1478)	(-0.2169 , 0.1986)	(-0.1387 , 0.1370)	**(0.0011 , 0.0056)***	(-0.0829 , 0.0504)	(-0.0820 , 0.1483)	(-0.0773 , 0.1438)
acatusa	(-0.0048 , 0.0057)	(-0.0913 , 0.1658)	(-0.2386 , 0.2235)	(-0.1369 , 0.1697)	**(0.0012 , 0.0058)***	(-0.0818 , 0.0535)	(-0.0854 , 0.1485)	(-0.0785 , 0.1460)
leupcbc	(-0.0034 , 0.0035)	(-0.0234 , 0.1445)	(-0.1720 , 0.1297)	(-0.0952 , 0.1049)	(-0.0003 , 0.0031)	(-0.0553 , 0.0436)	(-0.0849 , 0.0861)	(-0.0748 , 0.0894)
leupcbe	(-0.0037 , 0.0041)	(-0.0288 , 0.1610)	(-0.1987 , 0.1424)	(-0.1027 , 0.1236)	**(0.0002 , 0.0035)***	(-0.0588 , 0.0413)	(-0.0882 , 0.0849)	(-0.0769 , 0.0892)
leupcbu	(-0.0034 , 0.0049)	(-0.0408 , 0.1641)	(-0.1986 , 0.1696)	(-0.1180 , 0.1263)	**(0.0004 , 0.0037)***	(-0.0545 , 0.0420)	(-0.0816 , 0.0852)	(-0.0734 , 0.0867)
acatchi	(-0.0060 , 0.0039)	(-0.0825 , 0.1604)	(-0.2344 , 0.2021)	(-0.1493 , 0.1403)	**(0.0009 , 0.0056)***	(-0.0826 , 0.0577)	(-0.0763 , 0.1664)	(-0.0736 , 0.1593)
Panel B: Student-t(1)								
acatcha	(-0.0059 , 0.0033)	(-0.0870 , 0.1704)	(-0.2357 , 0.2101)	(-0.1795 , 0.1689)	**(0.0006 , 0.0050)***	(-0.0831 , 0.0614)	(-0.0771 , 0.1617)	(-0.0798 , 0.1641)
acateua	(-0.0044 , 0.0044)	(-0.0905 , 0.1549)	(-0.2216 , 0.2034)	(-0.1670 , 0.1653)	**(0.0013 , 0.0055)***	(-0.0843 , 0.0518)	(-0.0793 , 0.1456)	(-0.0816 , 0.1481)
acatusa	(-0.0045 , 0.0053)	(-0.0992 , 0.1737)	(-0.2439 , 0.2288)	(-0.1684 , 0.2012)	**(0.0014 , 0.0056)***	(-0.0833 , 0.0549)	(-0.0826 , 0.1458)	(-0.0829 , 0.1503)
leupcbc	(-0.0031 , 0.0033)	(-0.0286 , 0.1496)	(-0.1754 , 0.1332)	(-0.1158 , 0.1255)	(-0.0002 , 0.0030)	(-0.0564 , 0.0446)	(-0.0829 , 0.0841)	(-0.0779 , 0.0926)
leupcbe	(-0.0034 , 0.0038)	(-0.0346 , 0.1669)	(-0.2026 , 0.1463)	(-0.1260 , 0.1468)	**(0.0003 , 0.0034)***	(-0.0599 , 0.0424)	(-0.0862 , 0.0829)	(-0.0801 , 0.0924)
leupcbu	(-0.0031 , 0.0047)	(-0.0471 , 0.1704)	(-0.2028 , 0.1738)	(-0.1431 , 0.1514)	**(0.0005 , 0.0036)***	(-0.0555 , 0.0430)	(-0.0796 , 0.0832)	(-0.0765 , 0.0898)
acatchi	(-0.0056 , 0.0036)	(-0.0900 , 0.1679)	(-0.2394 , 0.2071)	(-0.1790 , 0.1700)	**(0.0010 , 0.0055)***	(-0.0841 , 0.0592)	(-0.0734 , 0.1636)	(-0.0781 , 0.1638)
Panel C: Student-t(2)								
acatcha	(-0.0060 , 0.0035)	(-0.0865 , 0.1699)	(-0.2331 , 0.2075)	(-0.1620 , 0.1514)	**(0.0005 , 0.0050)***	(-0.0807 , 0.0590)	(-0.0791 , 0.1638)	(-0.0779 , 0.1622)
acateua	(-0.0045 , 0.0045)	(-0.0900 , 0.1544)	(-0.2192 , 0.2009)	(-0.1503 , 0.1486)	**(0.0012 , 0.0055)***	(-0.0820 , 0.0496)	(-0.0812 , 0.1476)	(-0.0798 , 0.1463)
acatusa	(-0.0046 , 0.0055)	(-0.0987 , 0.1732)	(-0.2411 , 0.2261)	(-0.1498 , 0.1826)	**(0.0013 , 0.0056)***	(-0.0810 , 0.0526)	(-0.0846 , 0.1477)	(-0.0811 , 0.1485)
leupcbc	(-0.0032 , 0.0034)	(-0.0282 , 0.1492)	(-0.1736 , 0.1314)	(-0.1036 , 0.1133)	(-0.0002 , 0.0030)	(-0.0547 , 0.0430)	(-0.0843 , 0.0856)	(-0.0766 , 0.0912)
leupcbe	(-0.0035 , 0.0039)	(-0.0342 , 0.1665)	(-0.2006 , 0.1443)	(-0.1122 , 0.1331)	**(0.0003 , 0.0034)***	(-0.0582 , 0.0407)	(-0.0876 , 0.0843)	(-0.0788 , 0.0911)
leupcbu	(-0.0032 , 0.0048)	(-0.0466 , 0.1699)	(-0.2006 , 0.1717)	(-0.1282 , 0.1366)	**(0.0005 , 0.0036)***	(-0.0539 , 0.0414)	(-0.0810 , 0.0846)	(-0.0752 , 0.0885)
acatchi	(-0.0058 , 0.0037)	(-0.0895 , 0.1673)	(-0.2368 , 0.2045)	(-0.1615 , 0.1525)	**(0.0010 , 0.0055)***	(-0.0818 , 0.0569)	(-0.0755 , 0.1656)	(-0.0763 , 0.1620)
Panel D: Student-t(3)								
acatcha	(-0.0061 , 0.0036)	(-0.0826 , 0.1660)	(-0.2291 , 0.2035)	(-0.1546 , 0.1440)	**(0.0005 , 0.0051)***	(-0.0813 , 0.0596)	(-0.0745 , 0.1592)	(-0.0743 , 0.1585)
acateua	(-0.0047 , 0.0046)	(-0.0863 , 0.1508)	(-0.2154 , 0.1972)	(-0.1433 , 0.1415)	**(0.0012 , 0.0055)***	(-0.0826 , 0.0502)	(-0.0769 , 0.1432)	(-0.0764 , 0.1429)
acatusa	(-0.0047 , 0.0056)	(-0.0946 , 0.1691)	(-0.2369 , 0.2219)	(-0.1420 , 0.1748)	**(0.0013 , 0.0057)***	(-0.0816 , 0.0532)	(-0.0802 , 0.1433)	(-0.0776 , 0.1450)
leupcbc	(-0.0033 , 0.0034)	(-0.0256 , 0.1466)	(-0.1709 , 0.1287)	(-0.0985 , 0.1082)	(-0.0002 , 0.0030)	(-0.0552 , 0.0434)	(-0.0811 , 0.0823)	(-0.0741 , 0.0887)
leupcbe	(-0.0036 , 0.0040)	(-0.0312 , 0.1635)	(-0.1975 , 0.1412)	(-0.1065 , 0.1273)	**(0.0002 , 0.0035)***	(-0.0586 , 0.0411)	(-0.0844 , 0.0810)	(-0.0762 , 0.0885)
leupcbu	(-0.0033 , 0.0049)	(-0.0434 , 0.1667)	(-0.1973 , 0.1683)	(-0.1220 , 0.1304)	**(0.0005 , 0.0036)***	(-0.0543 , 0.0418)	(-0.0779 , 0.0815)	(-0.0727 , 0.0860)
acatchi	(-0.0059 , 0.0039)	(-0.0856 , 0.1635)	(-0.2329 , 0.2005)	(-0.1541 , 0.1451)	**(0.0009 , 0.0055)***	(-0.0824 , 0.0575)	(-0.0709 , 0.1610)	(-0.0727 , 0.1583)

Table 3.8 continued: Fama-French

CBMFs	11/2004 - 03/2011				04/2011 - 08/2014			
	CS(a)	**CS(b_{M})**	**CS(b_{SMB})**	**CS(b_{HML})**	**CS(a)**	**CS(b_{M})**	**CS(b_{SMB})**	**CS(b_{HML})**
Panel E: Student-t(4)								
acatcha	(-0.0062 , 0.0036)	(-0.0820 , 0.1654)	(-0.2275 , 0.2019)	(-0.1532 , 0.1426)	(0.0004 , 0.0051)*	(-0.0811 , 0.0594)	(-0.0806 , 0.1652)	(-0.0756 , 0.1598)
acateua	(-0.0047 , 0.0047)	(-0.0857 , 0.1501)	(-0.2138 , 0.1956)	(-0.1419 , 0.1402)	(0.0011 , 0.0056)*	(-0.0824 , 0.0499)	(-0.0826 , 0.1489)	(-0.0777 , 0.1441)
acatusa	(-0.0048 , 0.0056)	(-0.0939 , 0.1684)	(-0.2352 , 0.2201)	(-0.1405 , 0.1733)	(0.0012 , 0.0058)*	(-0.0814 , 0.0530)	(-0.0860 , 0.1491)	(-0.0789 , 0.1463)
leupcbc	(-0.0033 , 0.0035)	(-0.0251 , 0.1461)	(-0.1697 , 0.1275)	(-0.0976 , 0.1073)	(-0.0002 , 0.0031)	(-0.0550 , 0.0432)	(-0.0853 , 0.0866)	(-0.0750 , 0.0896)
leupcbe	(-0.0036 , 0.0040)	(-0.0307 , 0.1629)	(-0.1962 , 0.1399)	(-0.1054 , 0.1262)	(0.0002 , 0.0035)*	(-0.0585 , 0.0409)	(-0.0887 , 0.0853)	(-0.0772 , 0.0895)
leupcbu	(-0.0034 , 0.0049)	(-0.0429 , 0.1662)	(-0.1959 , 0.1669)	(-0.1208 , 0.1292)	(0.0005 , 0.0037)*	(-0.0541 , 0.0416)	(-0.0820 , 0.0856)	(-0.0736 , 0.0869)
acatchi	(-0.0059 , 0.0039)	(-0.0850 , 0.1628)	(-0.2312 , 0.1989)	(-0.1527 , 0.1437)	(0.0009 , 0.0056)*	(-0.0821 , 0.0572)	(-0.0769 , 0.1670)	(-0.0740 , 0.1596)
Panel F: Student-t(5)								
acatcha	(-0.0061 , 0.0036)	(-0.0812 , 0.1646)	(-0.2269 , 0.2013)	(-0.1554 , 0.1448)	(0.0004 , 0.0051)*	(-0.0815 , 0.0598)	(-0.0787 , 0.1633)	(-0.0755 , 0.1598)
acateua	(-0.0046 , 0.0046)	(-0.0850 , 0.1494)	(-0.2133 , 0.1950)	(-0.1440 , 0.1423)	(0.0012 , 0.0056)*	(-0.0828 , 0.0503)	(-0.0808 , 0.1471)	(-0.0776 , 0.1440)
acatusa	(-0.0047 , 0.0055)	(-0.0931 , 0.1676)	(-0.2346 , 0.2195)	(-0.1428 , 0.1756)	(0.0013 , 0.0057)*	(-0.0817 , 0.0534)	(-0.0842 , 0.1473)	(-0.0788 , 0.1462)
leupcbc	(-0.0033 , 0.0034)	(-0.0246 , 0.1456)	(-0.1694 , 0.1271)	(-0.0991 , 0.1088)	(-0.0002 , 0.0030)	(-0.0553 , 0.0435)	(-0.0840 , 0.0852)	(-0.0749 , 0.0896)
leupcbe	(-0.0036 , 0.0040)	(-0.0301 , 0.1623)	(-0.1958 , 0.1395)	(-0.1071 , 0.1279)	(0.0002 , 0.0035)*	(-0.0588 , 0.0412)	(-0.0873 , 0.0840)	(-0.0771 , 0.0894)
leupcbu	(-0.0033 , 0.0049)	(-0.0422 , 0.1655)	(-0.1954 , 0.1664)	(-0.1227 , 0.1310)	(0.0005 , 0.0037)*	(-0.0544 , 0.0419)	(-0.0807 , 0.0843)	(-0.0736 , 0.0868)
acatchi	(-0.0059 , 0.0038)	(-0.0842 , 0.1621)	(-0.2307 , 0.1983)	(-0.1549 , 0.1459)	(0.0009 , 0.0056)*	(-0.0825 , 0.0577)	(-0.0750 , 0.1651)	(-0.0739 , 0.1596)
Panel G: Student-t(6)								
acatcha	(-0.0061 , 0.0036)	(-0.0813 , 0.1647)	(-0.2284 , 0.2028)	(-0.1553 , 0.1447)	(0.0004 , 0.0052)*	(-0.0814 , 0.0597)	(-0.0782 , 0.1628)	(-0.0765 , 0.1608)
acateua	(-0.0047 , 0.0046)	(-0.0851 , 0.1495)	(-0.2147 , 0.1965)	(-0.1439 , 0.1422)	(0.0011 , 0.0056)*	(-0.0827 , 0.0502)	(-0.0804 , 0.1467)	(-0.0786 , 0.1450)
acatusa	(-0.0047 , 0.0056)	(-0.0932 , 0.1677)	(-0.2362 , 0.2212)	(-0.1427 , 0.1755)	(0.0012 , 0.0058)*	(-0.0817 , 0.0533)	(-0.0837 , 0.1468)	(-0.0798 , 0.1472)
leupcbc	(-0.0033 , 0.0034)	(-0.0247 , 0.1457)	(-0.1704 , 0.1282)	(-0.0990 , 0.1087)	(-0.0003 , 0.0031)	(-0.0552 , 0.0434)	(-0.0837 , 0.0849)	(-0.0757 , 0.0903)
leupcbe	(-0.0036 , 0.0040)	(-0.0302 , 0.1625)	(-0.1970 , 0.1407)	(-0.1070 , 0.1279)	(0.0001 , 0.0035)*	(-0.0587 , 0.0412)	(-0.0870 , 0.0836)	(-0.0778 , 0.0901)
leupcbu	(-0.0033 , 0.0049)	(-0.0423 , 0.1656)	(-0.1967 , 0.1677)	(-0.1226 , 0.1310)	(0.0004 , 0.0037)*	(-0.0543 , 0.0419)	(-0.0804 , 0.0840)	(-0.0743 , 0.0875)
acatchi	(-0.0059 , 0.0039)	(-0.0843 , 0.1622)	(-0.2322 , 0.1998)	(-0.1548 , 0.1458)	(0.0009 , 0.0056)*	(-0.0824 , 0.0576)	(-0.0745 , 0.1647)	(-0.0749 , 0.1606)
Panel H: Student-t(7)								
acatcha	(-0.0062 , 0.0037)	(-0.0802 , 0.1636)	(-0.2272 , 0.2016)	(-0.1515 , 0.1409)	(0.0004 , 0.0052)*	(-0.0826 , 0.0609)	(-0.0806 , 0.1653)	(-0.0756 , 0.1598)
acateua	(-0.0047 , 0.0047)	(-0.0840 , 0.1484)	(-0.2136 , 0.1953)	(-0.1403 , 0.1386)	(0.0011 , 0.0056)*	(-0.0838 , 0.0514)	(-0.0826 , 0.1489)	(-0.0776 , 0.1441)
acatusa	(-0.0048 , 0.0056)	(-0.0920 , 0.1665)	(-0.2349 , 0.2199)	(-0.1387 , 0.1715)	(0.0012 , 0.0058)*	(-0.0828 , 0.0545)	(-0.0860 , 0.1492)	(-0.0789 , 0.1463)
leupcbc	(-0.0033 , 0.0035)	(-0.0239 , 0.1449)	(-0.1696 , 0.1273)	(-0.0964 , 0.1061)	(-0.0003 , 0.0031)	(-0.0561 , 0.0443)	(-0.0853 , 0.0866)	(-0.0750 , 0.0896)
leupcbe	(-0.0037 , 0.0040)	(-0.0293 , 0.1615)	(-0.1960 , 0.1397)	(-0.1041 , 0.1249)	(0.0002 , 0.0035)*	(-0.0596 , 0.0420)	(-0.0887 , 0.0854)	(-0.0772 , 0.0895)
leupcbu	(-0.0034 , 0.0049)	(-0.0413 , 0.1646)	(-0.1957 , 0.1667)	(-0.1194 , 0.1278)	(0.0004 , 0.0037)*	(-0.0552 , 0.0427)	(-0.0820 , 0.0856)	(-0.0736 , 0.0869)
acatchi	(-0.0059 , 0.0039)	(-0.0832 , 0.1610)	(-0.2310 , 0.1986)	(-0.1510 , 0.1420)	(0.0009 , 0.0056)*	(-0.0837 , 0.0588)	(-0.0769 , 0.1670)	(-0.0740 , 0.1596)

Table 3.8 continued: Fama-French

CBMFs	11/2004 - 03/2011				04/2011 - 08/2014			
	CS(a)	**CS(b_M)**	**CS(b_{SMB})**	**CS(b_{HML})**	**CS(a)**	**CS(b_M)**	**CS(b_{SMB})**	**CS(b_{HML})**
Panel I: Student-t(8)								
acatcha	(-0.0062 , 0.0036)	(-0.0815 , 0.1650)	(-0.2304 , 0.2048)	(-0.1529 , 0.1423)	**(0.0004 , 0.0052)***	(-0.0821 , 0.0603)	(-0.0810 , 0.1656)	(-0.0746 , 0.1589)
acateua	(-0.0047 , 0.0047)	(-0.0853 , 0.1497)	(-0.2166 , 0.1983)	(-0.1416 , 0.1399)	**(0.0011 , 0.0056)***	(-0.0833 , 0.0508)	(-0.0830 , 0.1493)	(-0.0768 , 0.1432)
acatusa	(-0.0048 , 0.0056)	(-0.0935 , 0.1680)	(-0.2383 , 0.2232)	(-0.1401 , 0.1730)	**(0.0012 , 0.0058)***	(-0.0823 , 0.0539)	(-0.0863 , 0.1495)	(-0.0780 , 0.1454)
leupcbc	(-0.0033 , 0.0035)	(-0.0248 , 0.1458)	(-0.1718 , 0.1295)	(-0.0973 , 0.1071)	(-0.0003 , 0.0031)	(-0.0557 , 0.0439)	(-0.0856 , 0.0868)	(-0.0743 , 0.0890)
leupcbe	(-0.0036 , 0.0040)	(-0.0304 , 0.1626)	(-0.1985 , 0.1422)	(-0.1051 , 0.1260)	**(0.0001 , 0.0035)***	(-0.0592 , 0.0416)	(-0.0889 , 0.0856)	(-0.0765 , 0.0888)
leupcbu	(-0.0034 , 0.0049)	(-0.0425 , 0.1658)	(-0.1983 , 0.1694)	(-0.1206 , 0.1289)	**(0.0004 , 0.0037)***	(-0.0548 , 0.0423)	(-0.0823 , 0.0858)	(-0.0730 , 0.0862)
acatchi	(-0.0059 , 0.0039)	(-0.0845 , 0.1624)	(-0.2342 , 0.2018)	(-0.1524 , 0.1434)	**(0.0009 , 0.0056)***	(-0.0831 , 0.0582)	(-0.0773 , 0.1674)	(-0.0730 , 0.1587)
Panel J: Student-t(9)								
acatcha	(-0.0061 , 0.0035)	(-0.0801 , 0.1635)	(-0.2318 , 0.2062)	(-0.1511 , 0.1405)	**(0.0004 , 0.0052)***	(-0.0819 , 0.0602)	(-0.0793 , 0.1640)	(-0.0744 , 0.1586)
acateua	(-0.0046 , 0.0046)	(-0.0840 , 0.1484)	(-0.2179 , 0.1997)	(-0.1399 , 0.1382)	**(0.0011 , 0.0056)***	(-0.0832 , 0.0507)	(-0.0815 , 0.1478)	(-0.0765 , 0.1430)
acatusa	(-0.0047 , 0.0055)	(-0.0920 , 0.1664)	(-0.2397 , 0.2247)	(-0.1382 , 0.1710)	**(0.0012 , 0.0058)***	(-0.0821 , 0.0538)	(-0.0848 , 0.1480)	(-0.0777 , 0.1451)
leupcbc	(-0.0033 , 0.0034)	(-0.0238 , 0.1449)	(-0.1727 , 0.1305)	(-0.0961 , 0.1058)	(-0.0003 , 0.0031)	(-0.0556 , 0.0438)	(-0.0845 , 0.0857)	(-0.0742 , 0.0888)
leupcbe	(-0.0036 , 0.0039)	(-0.0293 , 0.1615)	(-0.1996 , 0.1433)	(-0.1037 , 0.1246)	**(0.0002 , 0.0035)***	(-0.0591 , 0.0415)	(-0.0878 , 0.0845)	(-0.0763 , 0.0886)
leupcbu	(-0.0033 , 0.0048)	(-0.0413 , 0.1646)	(-0.1995 , 0.1706)	(-0.1190 , 0.1274)	**(0.0004 , 0.0037)***	(-0.0547 , 0.0422)	(-0.0812 , 0.0847)	(-0.0728 , 0.0861)
acatchi	(-0.0058 , 0.0038)	(-0.0831 , 0.1610)	(-0.2355 , 0.2032)	(-0.1506 , 0.1416)	**(0.0009 , 0.0056)***	(-0.0830 , 0.0581)	(-0.0757 , 0.1658)	(-0.0728 , 0.1585)
Panel K: Student-t(10)								
acatcha	(-0.0062 , 0.0036)	(-0.0825 , 0.1659)	(-0.2252 , 0.1996)	(-0.1503 , 0.1397)	**(0.0004 , 0.0052)***	(-0.0813 , 0.0596)	(-0.0804 , 0.1650)	(-0.0756 , 0.1599)
acateua	(-0.0047 , 0.0047)	(-0.0862 , 0.1506)	(-0.2116 , 0.1934)	(-0.1391 , 0.1374)	**(0.0011 , 0.0056)***	(-0.0826 , 0.0501)	(-0.0824 , 0.1487)	(-0.0777 , 0.1441)
acatusa	(-0.0048 , 0.0056)	(-0.0944 , 0.1689)	(-0.2328 , 0.2177)	(-0.1374 , 0.1702)	**(0.0012 , 0.0058)***	(-0.0816 , 0.0532)	(-0.0858 , 0.1489)	(-0.0789 , 0.1463)
leupcbc	(-0.0033 , 0.0035)	(-0.0254 , 0.1465)	(-0.1682 , 0.1259)	(-0.0955 , 0.1053)	(-0.0003 , 0.0031)	(-0.0551 , 0.0434)	(-0.0852 , 0.0864)	(-0.0750 , 0.0896)
leupcbe	(-0.0036 , 0.0040)	(-0.0311 , 0.1633)	(-0.1944 , 0.1381)	(-0.1031 , 0.1240)	**(0.0002 , 0.0035)***	(-0.0586 , 0.0411)	(-0.0885 , 0.0852)	(-0.0772 , 0.0895)
leupcbu	(-0.0034 , 0.0049)	(-0.0433 , 0.1666)	(-0.1939 , 0.1650)	(-0.1184 , 0.1267)	**(0.0004 , 0.0037)***	(-0.0543 , 0.0418)	(-0.0819 , 0.0854)	(-0.0736 , 0.0869)
acatchi	(-0.0059 , 0.0039)	(-0.0855 , 0.1633)	(-0.2289 , 0.1966)	(-0.1498 , 0.1408)	**(0.0009 , 0.0056)***	(-0.0823 , 0.0574)	(-0.0767 , 0.1668)	(-0.0740 , 0.1597)
Panel L: Student-t(50)								
acatcha	(-0.0063 , 0.0037)	(-0.0796 , 0.1630)	(-0.2276 , 0.2020)	(-0.1504 , 0.1398)	**(0.0004 , 0.0052)***	(-0.0817 , 0.0600)	(-0.0814 , 0.1661)	(-0.0745 , 0.1588)
acateua	(-0.0048 , 0.0047)	(-0.0834 , 0.1479)	(-0.2139 , 0.1957)	(-0.1393 , 0.1375)	**(0.0011 , 0.0056)***	(-0.0829 , 0.0505)	(-0.0834 , 0.1497)	(-0.0767 , 0.1431)
acatusa	(-0.0049 , 0.0057)	(-0.0914 , 0.1659)	(-0.2353 , 0.2203)	(-0.1375 , 0.1703)	**(0.0012 , 0.0058)***	(-0.0819 , 0.0536)	(-0.0868 , 0.1499)	(-0.0779 , 0.1453)
leupcbc	(-0.0034 , 0.0035)	(-0.0235 , 0.1445)	(-0.1698 , 0.1276)	(-0.0956 , 0.1053)	(-0.0003 , 0.0031)	(-0.0554 , 0.0436)	(-0.0859 , 0.0871)	(-0.0743 , 0.0889)
leupcbe	(-0.0037 , 0.0041)	(-0.0288 , 0.1611)	(-0.1963 , 0.1400)	(-0.1032 , 0.1241)	**(0.0001 , 0.0035)***	(-0.0589 , 0.0414)	(-0.0892 , 0.0859)	(-0.0764 , 0.0887)
leupcbu	(-0.0034 , 0.0050)	(-0.0408 , 0.1641)	(-0.1960 , 0.1670)	(-0.1185 , 0.1268)	**(0.0004 , 0.0037)***	(-0.0545 , 0.0420)	(-0.0826 , 0.0862)	(-0.0729 , 0.0862)
acatchi	(-0.0060 , 0.0040)	(-0.0826 , 0.1604)	(-0.2314 , 0.1990)	(-0.1499 , 0.1409)	**(0.0009 , 0.0056)***	(-0.0827 , 0.0578)	(-0.0777 , 0.1678)	(-0.0729 , 0.1586)

Note: $CS(a)$, $CS(b_M)$, $CS(b_{SMB})$ and $CS(b_{HML})$ are exact, simultaneous confidence sets estimated for respectively intercepts, loadings on the excess market return, SMB and HML factors from the 3-factor Fama-French model. Panel A displays results obtained under Gaussian errors. Panels B-L contain estimates from the model with Student-t(η) errors under varying degrees of freedom, η.

* marks CS without zero. The significance level of all estimated CS is 5%.

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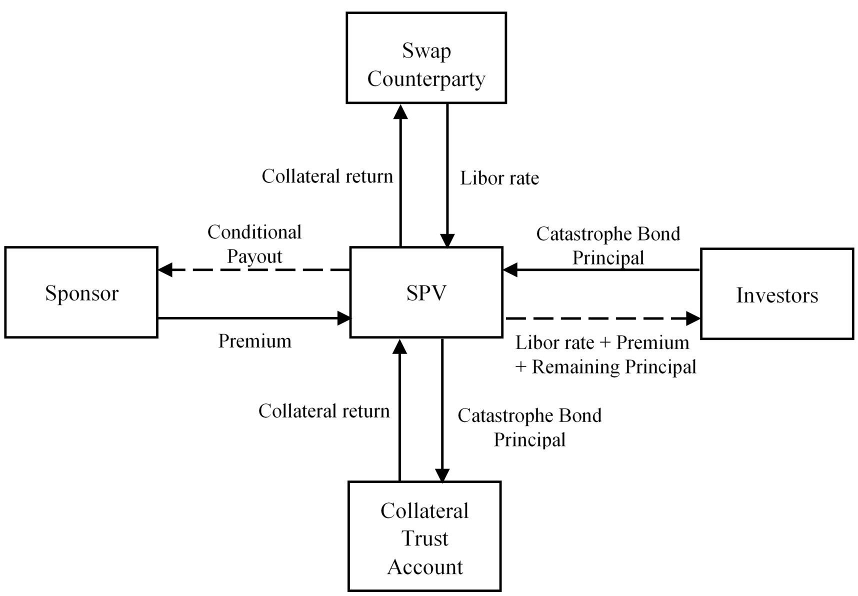
Appendices 3

A Catastrophe Bonds

First offered in mid-90s, Catastrophe bonds provide an alternative way to raise a risk capital for reinsurers and national governments for covering losses due to large-scale natural disasters, like tornadoes and earthquakes. With US $30 billion of outstanding capital in 2017, the market for Catastrophe bonds grew rapidly since its inception accounting for 30% of all global funding from alternative channels for property casualty reinsurance as of 2017 (Artemis, 2017; Aon Benfield, 2017b). Depicted in the Figure 3.A.1, the structure of a Catastrophe bond usually involves a sponsor, the party that initiates the bond, and a Special Purpose Vehicle (SPV), a separate entity created to manage the Catastrophe bond. Through an agreement specifying a default-triggering catastrophic event, the latter party assumes the catastrophe risk transfered over from the sponsor and issues a Catastrophe bond to be sold in financial markets. The funds from the bond sale are used to acquire highly-rated financial instruments, which are kept in the trust account as a collateral backing the Catastrophe bond.

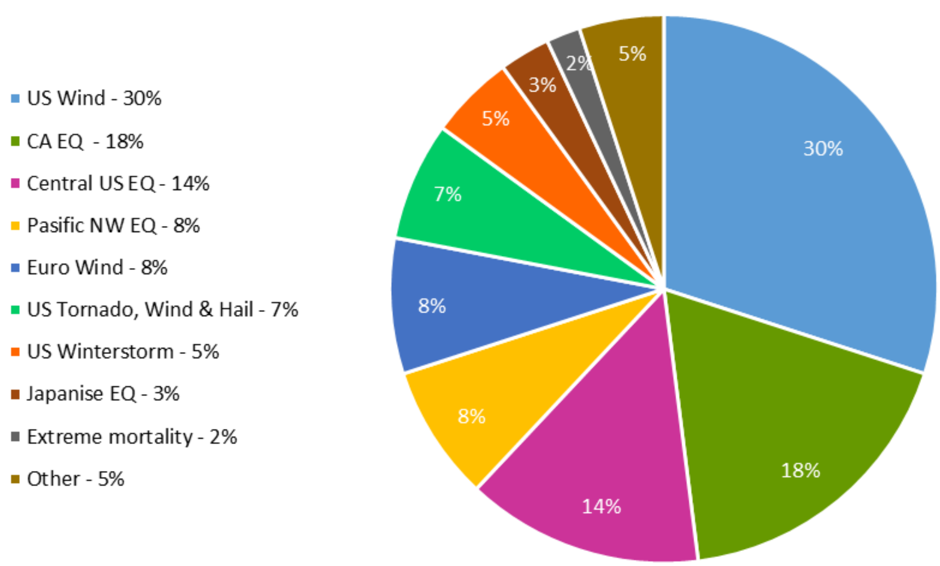
Figure 3.A.1: Design of a Catastrophe Bond



Bond investors benefit from the principal and a stream of regular coupon payments (premium and a floating interest rate) provided no default-triggering catastrophe takes place before the bond matures. In case of the latter, however, there could be a partial or a complete loss of coupons and the principal to investors with collateral assets sold off to make a payout to the bond sponsor in accordance with the agreement. Before the 2007-08 financial crisis, it was common for Catastrophe bonds to have a Total Return Swap Counterparty (TRSC) in their structure that would convert fixed returns on collateral assets into a floating interest rate, like Libor, and guarantee a payment of the principal to investors or the payout to the sponsor regardless of the value of the underlying collateral. The aim of involving the TRSC was to limit the exposure to the interest rate and collateral value risks. During the crisis, however, several Catastrophe bonds defaulted as the value of their collateral assets, largely mortgage-backed securities, plummeted and the Lehman Brothers, their TRSC, went bankrupt. Since then, Catastrophe bonds mostly rely on other controls instead of TRSC. These include limiting the list of admissible collateral assets to those that are highly liquid, transparent and safe like short-term government debt or government-backed instruments, stringent collateral monitoring and systematic investor updates.

For a typical Catastrophe bond, its default is contingent on a triggering variable reaching an ex ante determined limit. Variables that are usually used for this purpose include: indemnity triggers, which measure losses of a bond sponsor; index triggers, which are not sponsor-specific and instead condition a bond default on the value of some general index; parametric triggers involve physical attributes of a catastrophe; model loss triggers are obtained as simulation-based variables; hybrid triggers condition on several variables.

Figure 3.A.2: Allocation by catastrophe/region (as of July 1, 2012)

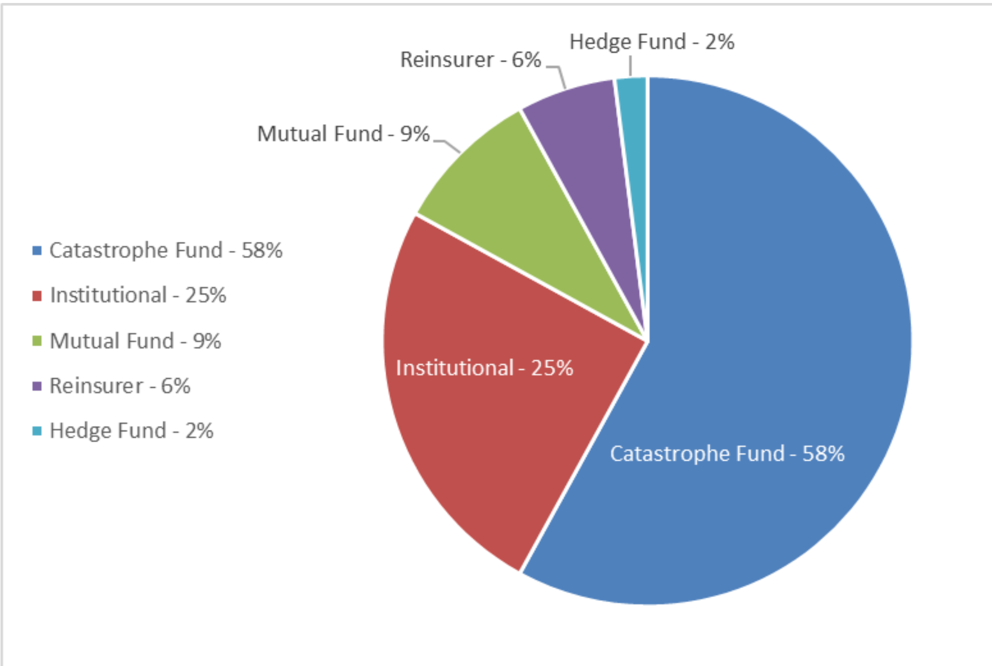


Source: Swiss Re (2012)− ILS Market Update, Vol. XVIII, July

Figure 3.A.2 displays the allocation of outstanding Catastrophe bonds across perils

and geographies as of mid-2012. 82% of all Catastrophe bonds cover US-based events. In particular, 30% of the bonds are allocated to the US windstorm, and 18% to the California earthquake. The shares captured by the Central US and the Pacific Northwest earthquakes are respectively 14% and 8%. US tornado and winterstorm represent another 7% and 5% of the coverage accordingly. The remaining capacity is allocated respectively to the Euro windstorm (8%), Japanese earthquake (3%), extreme mortality (2%) and other events (5%).

Figure 3.A.3: Investor profile for Catastrophe bonds (12 months preceding June 30, 2017)



Source: Aon Benfield (2017b)− Insurance-Linked Securities. Alternative Capital Breaks new boundaries. September 2017 Report.

As can be seen from the Figure 3.A.3, Catastrophe bonds attract funds from various sources, including a dominant share of capital received from external investors. CBMFs have the greatest allocation of Catastrophe bonds capturing nearly 60% of the primary market. There is also a considerable demand from institutional investors supplying 25% of the overall capacity. The allocation of mutual funds is 9%. Hedge funds hold another 2%. In terms of the internally raised capital, reinsurers purchased only 6% of the new issues.

B Analytical solution for exact, simultaneous confidence sets

Below, we restate the method of Beaulieu, Dufour and Khalaf (2018), which allows to produce analytically exact, simultaneous confidence sets for cross-sectional parameters on any regressor in the model (3.5) in a Gaussian setting. Extension to the Student-t case is also provided.

The analytical solution for computing confidence sets builds on the Hotelling statistic (3.9) defined for the joint null hypothesis in (3.7). Further, the distributional setting for the errors $U = [U_1, ..., U_n] = [\bar{U}_1, ..., \bar{U}_T]$ in the model (3.5) is given by:

$$\bar{U}_t = AZ_t, \quad t = 1, ..., T, \tag{B1}$$

such that matrix A is unknown and full-column and the $n \times 1$ vector Z_t is either jointly multivariate Gaussian

$$Z_t \sim iid\ N(0_n, \Sigma), \quad t = 1,\ \ldots\ ,\ T, \tag{B2}$$

or $i.i.d.$ Student-t($\bar{\eta}$), where $\bar{\eta}$ indicates known value for the degrees of freedom, as below

$$\begin{aligned} &Z_t = H_{1t}/(H_{2t}/\bar{\eta})^{1/2}, \quad t = 1,\ \ldots\ ,\ T, \\ &H_{1t} \sim N[0, I_n], \quad H_{2t} \sim \chi^2(\bar{\eta}), \end{aligned} \tag{B3}$$

such that H_{1t} and H_{2t} are independent.

Given a non-zero k-dimensional column vector τ and a significance level α, denote by $\tau'\theta_s$ a linear transformation of θ_s with a corresponding confidence set given by $CS_\alpha(\tau'\theta_s)$.

In this setting, the first step in constructing exact, simultaneous confidence sets for $\tau'\theta_s$ is to invert the Hotelling test given by (3.11). This requires considering all admissible values of θ_s iteratively. For each particular parameter choice $\bar{\theta}_s$, the respective estimate of the test statistic $\Psi(\bar{\theta}_s)$ is obtained using (3.9). If the latter satisfies inequality (3.11) at a significance level α, the associated value of $\bar{\theta}_s$ is retained to construct a $(1-\alpha)$ joint confidence region for θ_s. Given the α significance level, the inequality (3.11) is defined using the threshold point, $g_{n,d,\alpha}$, from the Fisher distribution when errors are Gaussian or its simulation-based counterpart in the Student-t($\bar{\eta}$) case. The simulated cut-off point obtains as an α-level value from the null distribution for the Hotelling statistic simulated in the Student-t setting. The Appendix C describes the procedure for producing the simulation-based cut-off value. Retrieving confidence sets for each component of $w_s = \tau'\theta_s$ involves locating its respective maximum and minimum over all values of θ_s within the joint region.

Implementing these steps analytically requires restating the inequality (3.11) as follows:

$$\bar{\theta}_s' Q_{22} \bar{\theta}_s + 2Q_{12}\bar{\theta}_s + Q_{11} \leq 0 \tag{B4}$$

which has an closed-form solution proposed in a Gaussian setting by Beaulieu, Dufour and Khalaf (2018) based on the quadrics approach of Dufour and Taamouti (2005). The elements of this quadratic inequality are given by an n-dimensional square matrix Q_{22}, a $n \times 1$ vector Q_{12} and a scalar Q_{11}:

$$Q_{22} = \hat{S}^{-1},\ Q_{12} = -\hat{\theta}_s \hat{S}^{-1},\ Q_{11} = \hat{\theta}_s' S^{-1} \hat{\theta}_s - \frac{n}{d} g_{n,d,\alpha} \left(\rho_k[s]'(X'X)^{-1}\rho_k[s]\right) \tag{B5}$$

with $\hat{\theta}_s$ and $\hat{S}$ corresponding to respectively OLS estimator of MLR coefficients and the sum of squared residuals given by (3.8). Also, $d = T - k - n + 1$ and $\rho_k[s]$ is a $k \times 1$ vector with the entry s equal one and all other observations set to zero. In a Gaussian setting, the α-level cut-off point $g_{n,d,\alpha}$ is retrieved from the Fisher distribution. For the case with *i.i.d.* jointly multivariate Student-t($\bar{\eta}$) errors, we propose to extend the method of Beaulieu, Dufour and Khalaf (2018) by setting $g_{n,d,\alpha}$ to the simulation-based cut-off point estimated as described in the Appendix C.

Setting $\tilde{Q} = -Q_{22}^{-1}Q_{12}'$, $B = Q_{12}'Q_{22}^{-1}Q_{12} - Q_{11}$, a confidence set $CS_\alpha(\tau'\theta_s)$ takes the following form:

- when Q_{22} has only positive eigenvalues:

$$CS_\alpha(\tau'\bar{\theta}_s) = \left[\tau'\tilde{Q} - \sqrt{B\tau' Q_{22}^{-1}\tau},\quad \tau'\tilde{Q} + \sqrt{B\tau' Q_{22}^{-1}\tau}\right],\quad \text{if } B \geq 0 \tag{B6}$$

$$CS_\alpha(\tau'\bar{\theta}_s) = \emptyset,\quad \text{if } B < 0 \tag{B7}$$

- when Q_{22} is invertible and one of its eigenvalues is below zero:

  (a) if $\tau' Q_{22}^{-1}\tau < 0$ and $B < 0$:

$$CS_\alpha(\tau'\bar{\theta}_s) = \left]-\infty,\ \tau'\tilde{Q} - \sqrt{B\tau' Q_{22}^{-1}\tau}\right] \cup \left[\tau'\tilde{Q} + \sqrt{B\tau' Q_{22}^{-1}\tau},\ +\infty\right[\tag{B8}$$

  (b) if $\tau' Q_{22}^{-1}\tau > 0$ or if $\tau' Q_{22}^{-1}\tau \leq 0$ and $B \geq 0$:

$$CS_\alpha(\tau'\bar{\theta}_s) = \mathbb{R} \tag{B9}$$

  (c) if $\tau' Q_{22}^{-1}\tau = 0$ and $B < 0$:

$$CS_\alpha(\tau'\bar{\theta}_s) = \mathbb{R}\backslash\{\tau'\tilde{Q}\} \tag{B10}$$

- when Q_{22} is invertible with more than one eigenvalue below zero:

$$CS_\alpha(\tau'\bar{\theta}_s) = \mathbb{R}. \tag{B11}$$

The resulting confidence set for $\tau'\theta_s$ is always a bounded interval as in (B6) since $Q_{22} =$

$\hat{S}^{-1}$ and B is given by:

$$
\begin{aligned}
B &= Q_{12}' Q_{22}^{-1} Q_{12} - Q_{11} \\
&= \hat{\theta}_s' S^{-1} \hat{\theta}_s - \left[\hat{\theta}_s' S^{-1} \hat{\theta}_s - \frac{n}{d} g_{n,d,\alpha} \left(\rho_k[s]'(X'X)^{-1} \rho_k[s] \right) \right] \\
&= \frac{n}{d} g_{n,d,\alpha} \left(\rho_k[s]'(X'X)^{-1} \rho_k[s] \right).
\end{aligned}
$$

C Simulated cut-off for the Hotelling test with Student-t errors

Given the MLR model (3.5) and unknown, full-column matrix A, consider the following specification for the errors $U = [U_1, ..., U_n] = [\bar{U}_1, ..., \bar{U}_T]$:

$$
\bar{U}_t = A Z_t, \quad t = 1, ..., T, \tag{C1}
$$

and

$$
\begin{aligned}
& Z_t = H_{1t}/(H_{2t}/\bar{\eta})^{1/2}, \quad t = 1, \; \ldots \; , \; T, \\
& H_{1t} \sim N[0, I_n], \quad H_{2t} \sim \chi^2(\bar{\eta}),
\end{aligned} \tag{C2}
$$

such that H_{1t} and H_{2t} are independent and $\bar{\eta}$ denotes a known value for the degrees of freedom parameter η.

Further, let $h = \bar{\theta}_s$ and denote by $K = e_k[s]'$ a k-dimensional column vector with zero in each cell except for the unity contained in the entry s. Then we can restate the joint null hypothesis (3.7) as

$$
H_0 : K\Theta = h, \tag{C3}
$$

with its associated Hotelling statistic in (3.9) taking the following form

$$
\begin{aligned}
\Psi(\bar{\theta}_s) &= [K(X'X)^{-1}K']^{-1}(K\theta - h)(\hat{U}'\hat{U})^{-1}(K\theta - h)' \frac{d}{n} \\
&= \left\{ [K(X'X)^{-1}K']^{-1}(K\theta - h)(\hat{U}'\hat{U})^{-1}(K\theta - h)' + 1 - 1 \right\} \frac{d}{n}.
\end{aligned}
$$

Since the determinant of a scalar is that scalar, it follows that

$$
\Psi(\bar{\theta}_s) = \left\{ |[K(X'X)^{-1}K']^{-1}(K\theta - h)(\hat{U}'\hat{U})^{-1}(K\theta - h)' + 1| - 1 \right\} \frac{d}{n},
$$

and we can further rewrite the latter expression as[6]

$$
\begin{aligned}
\Psi(\bar{\theta}_s) &= \left\{\left|(\hat{U}'\hat{U})^{-1}(K\theta-h)[K(X'X)^{-1}K']^{-1}(K\theta-h)'+I_n\right|-1\right\}\frac{d}{n} \\
&= \left\{\left|(\hat{U}'\hat{U})^{-1}(\hat{U}_0'\hat{U}_0-\hat{U}'\hat{U})+I_n\right|-1\right\}\frac{d}{n} \\
&= \left\{\left|(\hat{U}'\hat{U})^{-1}\hat{U}_0'\hat{U}_0-(\hat{U}'\hat{U})^{-1}\hat{U}'\hat{U}+I_n\right|-1\right\}\frac{d}{n} \\
&= \left\{\left|(\hat{U}'\hat{U})^{-1}\hat{U}_0'\hat{U}_0-I_n+I_n\right|-1\right\}\frac{d}{n} \\
&= \left\{\left|\hat{U}_0'\hat{U}_0(\hat{U}'\hat{U})^{-1}\right|-1\right\}\frac{d}{n} \\
&= \left\{\left|\hat{U}_0'\hat{U}_0\right|\left|(\hat{U}'\hat{U})^{-1}\right|-1\right\}\frac{d}{n} \\
&= \left\{\frac{|\hat{U}_0'\hat{U}_0|}{|(\hat{U}'\hat{U})|}-1\right\}\frac{d}{n}, \qquad \text{(C4)}
\end{aligned}
$$

where in the 2nd line we apply the result available in the literature that $(D\theta-z)[K(X'X)^{-1}K']^{-1}(K\theta-h)'=(\hat{U}_0'\hat{U}_0-\hat{U}'\hat{U})$ (refer, for instance, to Dufour and Khalaf, 2002). In the latter expression, $\hat{U}_0'\hat{U}_0$ and is the quasi maximum likelihood estimator (QMLE) for $U'U$ under (C3) and $\hat{U}'\hat{U}$ is the QMLE for $U'U$ in the case without restrictions.

Since $\hat{U}=PU$ and $\hat{U}_0=P_0U$ [see, e.g., Dufour and Khalaf (2002)] where $P=I_T-X(X'X)^{-1}X'$ and $P_0=P+X(X'X)^{-1}K'[K(X'X)^{-1}K']^{-1}K(X'X)^{-1}X'$, the expression in (C4) can be further transformed as follows:

$$\Psi(\bar{\theta}_s)=\left\{\frac{|U'P_0U|}{|U'PU|}-1\right\}\frac{d}{n}. \qquad \text{(C5)}$$

Since (C1) implies that $Z=U(A^{-1})'$, for the term in the denominator, it is the case that:

$$
\begin{aligned}
U'PU &= A[U(A^{-1})']'P[U(A^{-1})]'A' \\
&= AZ'PZA'. \qquad \text{(C6)}
\end{aligned}
$$

Similarly, for the numerator we have:

$$U'P_0U=AZ'P_0ZA'. \qquad \text{(C7)}$$

[6]Given $(c\times d)$ matrix P and $(d\times c)$ matrix V, it is the case that $|I_c+PV|=|I_d+VP|$. This result is available in (Harville, 1997, Chapter 18).

Substituting (C6) and (C7) into (C5) produces:

$$\begin{aligned}\Psi(\bar{\theta}_s) &= \left\{\frac{|AZ'P_0ZA'|}{|AZ'PZA'|} - 1\right\}\frac{d}{n} \\ &= \left\{\frac{|A||Z'P_0Z||A'|}{|A||Z'PZ||A'|} - 1\right\}\frac{d}{n} \\ &= \left\{\frac{|Z'P_0Z|}{|Z'PZ|} - 1\right\}\frac{d}{n}.\end{aligned}$$

It then follows:

$$\Psi(\bar{\theta}_s) = (\Gamma - 1)\frac{d}{n}, \quad \Gamma = \frac{|Z'P_0Z|}{|Z'PZ|}. \tag{C8}$$

Implementing the following two steps allows to simulate a null distribution for the statistic $\Psi(\bar{\theta}_s)$ written as in (C8):
(1) Retrieve a series of arrays $Z_t^{(l)}$, $l = 1, ..., L$, from *i.i.d.* jointly multivariate Student-t($\bar{\eta}$) distribution with $\bar{\eta}$ denoting a known value for the degrees of freedom parameter η.
(2) At each draw l, use the associated data in $Z_t^{(l)}$ and the observed sample to obtain an estimate of the statistic given (C8).

Iterating over all l yields L simulation-based statistics. After sorting the latter, the α-level value of the statistic is selected as an appropriate simulation-based critical value.

D Combined Goodness-of-Fit test

CGF Test Statistic

To evaluate a joint null hypothesis of skewness and kurtosis confined to values of their equivalents in the distribution assumed for errors we use the the Combined Goodness-of-Fit (CGF) test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013) reproduced below.

Denote by A an unknown, full-column matrix. Given the model (3.5), consider the following distributional setting for the errors $U = [U_1, ..., U_n] = [\bar{U}_1, ..., \bar{U}_T]$:

$$\bar{U}_t = AZ_t, \quad t = 1, ..., T, \tag{D1}$$

where Z_t either consists of n $i.i.d.$ jointly multivariate Normal variables

$$Z_t \sim iid\ N(0_n, \Sigma), \quad t = 1,\ \dots\ ,\ T, \tag{D2}$$

or has a distribution known up to a nuisance parameter π. The latter corresponds to the degrees of freedom parameter η when Z_t are $i.i.d.$ jointly multivariate Student-t(η):

$$\begin{aligned} &Z_t = H_{1t}/(H_{2t}/\eta)^{1/2}, \quad t = 1,\ \dots\ ,\ T, \\ &H_{1t} \sim N[0, I_n], \quad H_{2t} \sim \chi^2(\eta), \end{aligned} \tag{D3}$$

where H_{1t} and H_{2t} are independent.

Let $\hat{p}_N(\cdot)$ indicate an exact p-value computed using the Monte Carlo (MC) method (Dwass, 1957; Barnard, 1963; Dufour, 2006) as summarized in the Appendix C. Also, denote by $\bar{\pi}$ a known value of a nuisance parameter π.

The CGF test relies on the following statistic:

$$\Phi(\bar{\pi}) = 1 - min\{\hat{p}_N(E_S(\bar{\pi})), \hat{p}_N(E_K(\bar{\pi}))\}, \tag{D4}$$

with $\hat{p}_N(E_S(\tilde{\pi}))$ and $\hat{p}_N(E_K(\tilde{\pi}))$ denoting exact MC p-values for respectively excess skewness and kurtosis criteria given by:

$$E_S(\bar{\pi}) = |S - \overline{S}(\bar{\pi})|, \quad E_K(\bar{\pi}) = |K - \overline{K}(\bar{\pi})|, \tag{D5}$$

where S and K are respectively skewness and kurtosis measures (Mardia, 1970) defined below with their associated simulation-based expectations $\overline{S}(\bar{\pi})$ and $\overline{K}(\bar{\pi})$ estimated as described in E.1.1:

$$S = T^{-2} \sum_{j=1}^{T} \sum_{t=1}^{T} \hat{w}_{jt}^3, \quad K = T^{-1} \sum_{t=1}^{T} \hat{w}_{tt}^2. \tag{D6}$$

Values $\hat{w}_{jt}$ and $\hat{w}_{tt}$ are from the matrix $\hat{W} = T\hat{U}(\hat{U}'\hat{U})^{-1}\hat{U}'$ where $\hat{U}$ collects OLS residuals. In Gaussian setting, the excess skewness and kurtosis statistics simplify to $E_S = |S - \overline{S}|$ and $E_K = |K - \overline{K}|$ accordingly.

Beaulieu, Dufour and Khalaf (2003) demonstrate the pivotality of statistics S and K as their distributions coincide respectively with those for the following two pivotal measures:

$$w_S = T^{-2}\sum_{j=1}^{T}\sum_{t=1}^{T} w_{jt}^3, \quad w_K = T^{-1}\sum_{t=1}^{T} w_{tt}^2 \tag{D7}$$

with terms w_{jt} retrieved from the matrix

$$W = TDZ(Z'DZ)^{-1}Z'D, \quad Z = \left[Z_1, \ \dots \ , Z_T\right]', \quad D = I - X(X'X)^{-1}X', \tag{D8}$$

Modified statistics $E_S(\bar{\pi})$ and $E_K(\bar{\pi})$ retain the pivotality of the underlying measures. As such, their exact p-values, $\hat{p}_N(E_S(\bar{\pi})$ and $\hat{p}_N(E_K(\bar{\pi}))$, could be obtained via the MC method (Dwass, 1957; Barnard, 1963; Dufour, 2006) (reproduced below in C) given steps summarized in E.1.1 and E.2.1-E.2.4. Further, the procedure for computing an exact MC p-value for the joint CGF test statistic $\Phi(\bar{\pi})$ is restated in E.3.1-E.3.6.

Monte Carlo Method

This part of the appendix contains a summary of the MC method of (Dwass, 1957; Barnard, 1963; Dufour, 2006). Consider the model (3.5) and the distributional setting given by (D1)-(D3) and denote by α a chosen significance level. Provided that there is a pivotal transformation for a test statistic $M(y, X)$:

$$M(y, X) = \bar{M}(Z, X)$$

under the null hypothesis, the following MC formula can be applied to produce its exact p-value, denoted as $\hat{p}_J[M] = p_J[M^{(0)}, M]$, such that $M^{(0)}$ is the estimate of the statistic given a dataset of collected observations:

$$p_J[v, M] \equiv \frac{1 + \sum_{j=1}^{J} I_+\left[M^{(j)} - v\right]}{1 + J} \tag{D9}$$

such that

$$I_+\left[M^{(j)} - v\right] = \begin{cases} 1, & \text{if } \left[M^{(j)} - v\right] \geq 0, \\ 0, & \text{if } \left[M^{(j)} - v\right] < 0. \end{cases} \tag{D10}$$

where $M^{(j)}$ is the value of the statistic that depends on the simulated observations $Z_{(j)} = \left[Z_1^{(j)}, \ \dots \ , Z_n^{(j)}\right]$, $j = 1, \ \dots \ , J$ retrieved from Z in a series of J *i.i.d.* draws.

Given the MC critical region $\hat{p}_J[M] \leq \alpha$, $0 < \alpha < 1$, the following probability statement holds exactly

$$P[\hat{p}_J[M] \leq \alpha] = \alpha \tag{D11}$$

under the null hypothesis so long as $\alpha(J+1)$ is an integer and M has a continuous null distribution.

E Implementation of the CGF test

Implementing the CGF test of Beaulieu, Dufour and Khalaf (2003, 2007, 2013) proceeds in the setting defined by equations (3.5) and (D1)-(D3) with π fixed to a known value $\bar{\pi}$ and entails the following three step procedure.

Simulated Moments

E.1.1 Given the simulated data $\tilde{Z}_{(c)} = \left[\tilde{Z}_1^{(c)}, \ \ldots \ , \tilde{Z}_n^{(c)}\right]$ drawn from Z as a series of C *i.i.d.* realizations, $c = 1, ..., C$, with $\pi = \bar{\pi}$, compute the associated matrices:

$$W_{(c)} = TD\tilde{Z}_{(c)}(\tilde{Z}'_{(c)}D\tilde{Z}_{(c)})^{-1}\tilde{Z}'_{(c)}D, \quad D = I - X(X'X)^{-1}X', \quad c = 1, \ \ldots \ , \ C, \tag{E1}$$

and use these to estimate C respective simulation-based statistics $S_{(c)}(\bar{\pi})$ and $K_{(c)}(\bar{\pi})$ given (D6). The simulated first moments for the skewness and kurtosis measures are then obtained as below:

$$\overline{S}(\bar{\pi}) = C^{-1}\sum_{c=1}^{C} S_{(c)}(\bar{\pi}), \quad \overline{K}(\bar{\pi}) = C^{-1}\sum_{c=1}^{C} K_{(c)}(\bar{\pi}), \quad c = 1, ..., C. \tag{E2}$$

Individual Statistics

E.2.1 Compute simulated moments for the skewness and kurtosis measures, $\overline{S}(\bar{\pi})$ and $\overline{K}(\bar{\pi})$, as described in E.1.1.
E.2.2 Using the observed data and the simulation-based expectations from the previous step, obtain the excess skewness and kurtosis statistics given the formulas in (D5) denoting resulting estimates as $E^{(0)} = [E_S^{(0)}(\bar{\pi}), E_K^{(0)}(\bar{\pi})]'$.
E.2.3 Simulate new data $Z_{(l)} = \left[Z_1^{(l)}, \ \ldots \ , Z_n^{(l)}\right]$, $l = 1, \ \ldots \ , \ L$, by making a series of L *i.i.d.* draws from Z holding $\pi = \bar{\pi}$. Based on each matrix $Z_{(l)}$ and the simulated moments from E.2.1, estimate the associated L statistics $E^{(l)} = [E_S^{(l)}(\bar{\pi}), E_K^{(l)}(\bar{\pi})]'$, $l = 1, \ \ldots \ , \ L$ as in (D5).
E.2.4 Using L simulation-based statistics from the last step and the observed statistics $E^{(0)}$, obtain the exact, MC p-value for the excess skewness and kurtosis statistics, denoted

respectively by $\hat{p}_N(E_S(\bar{\pi}))$ and $\hat{p}_N(E_K(\bar{\pi}))$, as in (D9) and (D10). Values of $\hat{p}_N(E_S(\bar{\pi}))$ below α signal a rejection of the individual null hypothesis restricting the skewness at a significance level α. Testing for the kurtosis involves a similar rule.

Combined Statistic

E.3.1 Estimate simulation-based expectations for the skewness and kurtosis, $\overline{S}(\bar{\pi})$ and $\overline{K}(\bar{\pi})$, as in E.1.1.
E.3.2 Retrieve J simulated samples in a series of $i.i.d.$ draws from Z with $\pi = \bar{\pi}$. Use this newly generated data and the moments simulated in E.3.1 to produce J associated excess skewness and kurtosis statistics $E^{(j)} = [E_S^{(j)}(\bar{\pi}), E_K^{(j)}(\bar{\pi})]'$, $j = 1, \ldots, J$, by applying formulas in (D5).
E.3.2 Using the formula in (D9), produce two MC p-value functions, one for the excess skewness and one for the excess kurtosis criteria, each expressed in terms of J associated simulated statistics from the last step: $p_J(v, M)$ with $M = E_S(\bar{\pi}), E_K(\bar{\pi})$.
E.3.3 Based on the simulated moments from step E.3.1 and the observed sample, obtain the values of the excess skewness and kurtosis as in (D5) denoting the estimates by $E^{(0)} = [E_S^{(0)}(\bar{\pi}), E_K^{(0)}(\bar{\pi})]'$.
E.3.4 Produce another set of J_1 simulated samples through a series of $i.i.d.$ draws from Z fixing $\alpha(J_1 + 1)$ to be an integer and holding $\pi = \bar{\pi}$. Use these J_1 realizations of Z and the simulated moments from E.3.1 to obtain the associated excess skewness and kurtosis statistics given (D5): $E^{(i)} = [E_S^{(i)}(\bar{\pi}), E_K^{(i)}(\bar{\pi})]'$, $i = 1, \ldots, J_1$.
E.3.5 Plug in $E^{(0)}$ from E.3.3 and J_1 simulation-based statistics $E^{(i)}$ from the previous step into the two p-value functions from E.3.2 to generate exact, MC p-values on the excess skewness and kurtosis tests denoting these respectively as $\hat{p}_J^{(0)}(M) = \hat{p}_J(M^{(0)}, M)$ and $\hat{p}_J^{(i)}(M) = \hat{p}_J(M^{(i)}, M)$ with $M = E_S(\bar{\pi}), E_K(\bar{\pi})$ and given $i = 1, \ldots, J_1$.
E.3.6 Given p-values from E.3.5, compute $J_1 + 1$ estimates of the CGF test statistic as follows:

$$\Phi^{(m)}(\bar{\pi}) = 1 - min\{\hat{p}_J^{(m)}(E_S(\bar{\pi})), \hat{p}_J^{(m)}(E_K(\bar{\pi}))\}, \quad m = 0, 1, 2, ..., J_1 \tag{E3}$$

and plug these into the MC formula (D9) to estimate the exact p-value for the CGF test, denoted as $\hat{p}_{J_1}(\Phi(\bar{\pi})) = p_{J_1}(\Phi^{(0)}(\bar{\pi}), \Phi(\bar{\pi}))$. When the latter falls below α, the CGF test is said to be significant at a significance level α.

F Mimicking portfolio

This appendix summarizes a common approach for constructing a mimicking portfolio to replace a non-tradable risk factor in financial models. We apply this procedure to obtain a portfolio that mimics the squared market return to be used in the QCAPM as a risk factor. As theorized by Breeden (1979) and Huberman, Kandel and Stambaugh (1987), portfolios that mimic non-tradable factors could be used in their place for inference in financial models. A usual practice in the literature is to obtain a mimicking portfolio for a non-tradable factor as a weighted average of returns on benchmark assets that do a good job at generating the same efficiency frontier as the one based on all assets (i.e., spanning). To this end, weights are obtained as a function of slope coefficients from the regression of a non-tradable factor on a constant and benchmark returns (see, e.g., Breeden, Gibbons and Litzenberger, 1989; Adrian, Etula and Tyler, 2014). Formally, this regression is given by:

$$\tilde{Y}_t = a + b'H_t + v_t, \quad t = 1, ..., T, \tag{F1}$$

where $\tilde{Y}_t$ is a scalar observation on a non-tradable factor and H_t is a $h \times 1$ vector of base asset returns expressed in deviation from the risk-free rate. As suggested by Adrian, Etula and Tyler (2014), we use six Fama-French portfolios with a sorting on size and book-to-market, the momentum factor and the 10-year US Treasury bond yield as base assets to obtain the mimicking portfolio on the squared market return.

Given the OLS estimates $\hat{b}_j$, $j = 1, ..., h$, for coefficients in b, a projection-based mimicking portfolio $M\tilde{Y}_t$ for a non-tradable factor $\tilde{Y}_t$ can be constructed as follows, $j = 1, ..., h, \quad t = 1, ..., T$:

$$\begin{aligned} M\tilde{Y}_t &= \hat{w}'H_t, \\ \hat{w} &= (\hat{w}_1, ..., \hat{w}_h)', \quad \hat{w}_j = \frac{\hat{b}_j}{\sum_{j=1}^{g} \hat{b}_j}. \end{aligned} \tag{F2}$$

Chapter Four

Endogeneity in a zero-beta analysis: joint, finite sample inference on Catastrophe bond mutual funds

4.1 Introduction

Given low correlations between catastrophic events and financial assets, investors may perceive Catastrophe bond mutual funds [**CBMFs**] as zero-beta assets with little exposure to the systematic market risk (Litzenberger et al., 1996; LGT Capital Partners, 2015). In terms of their investment portfolio, these funds primarily focus on various Catastrophe bonds and offer diversification across disaster events and territories covered.[1] An investment in a Catastrophe bond yields regular coupons until expiry and principal at maturity unless the bond defaults due to an occurrence of a triggering catastrophe, like earthquake or winterstorm. Given that default of underlying securities is primarily tied to natural disasters, CBMFs may co-move little with financial markets. Providing evidence to the contrary, several Catastrophe bonds defaulted during the 2007-08 financial crisis due to an extreme exposure to the counterparty default and the collateral value risks. In turn, the entire market for Catastrophe bonds and that for CBMFs were affected. As such, it is not necessarily evident that CBMFs are in fact zero-beta. Using exact, multivariate methods that allow us to jointly test for and take into account the endogeneity of risk factors, we formally examine whether CBMFs perform as zero-beta assets.

Several reasons for robust inference on the zero-beta performance of CBMFs are particularly relevant. First, insufficient evidence on the dynamics of CBMFs vis-a-vis financial markets may lead to mis-pricing of funds, thus undermining the stability of the financial system, particularly if price corrections for CBMFs occur during severe market-wide financial stress. Given USD $30 billion of Catastrophe bonds outstanding in 2017 with nearly 60% share of all new bond issues captured by CBMFs, there could be a pronounced contribution to the overall financial instability, particularly when compounded with other risks and vulnerabilities (Artemis, 2017; Aon Benfield, 2017b). Second, there could be a considerable impact in terms of negative social outcomes if investments are managed based on an insufficient information and unrealistic expectations about the performance of CBMFs. Third, CBMFs indirectly contribute to the stability of reinsurance markets. In particular, through their large holdings of Catastrophe bonds (at least 75% of the overall funds' portfolio), CBMFs provide a large share of all alternative risk capital for the

[1] Appendix A describes Catastrophe bonds in more detail.

reinsurance markets. Given that Catastrophe bonds accounted for nearly 30% of global funding for property catastrophe reinsurance obtained from alternative channels in 2017, the impact of CBMFs on the efficient functioning of reinsurance markets is considerable (Aon Benfield, 2017a). As such, robust inference on CBMFs could help promote stability in financial and reinsurance sectors and help investors in managing their portfolios.

Though important, the issue of whether CBMFs are zero-beta gained little attention in the literature thus far. Through a panel data analysis of CBMFs before mid-2008, Cummins and Weiss (2009) discover a positive, statistically significant association of the funds with stock and corporate bond benchmarks. The estimated factor loadings are, however, economically trivial suggesting that CBMFs may have performed close to zero-beta assets before mid-2008. Rather than assessing CBMFs, related studies have examined the link between Catastrophe bonds or their market index with financial market benchmarks (Cummins and Weiss, 2009; Gürtler, Hibbeln and Winkelvos, 2014; Gomez and Carcamo, 2014; Carayannopoulos and Perez, 2015; Braun, 2015). According to their findings, Catastrophe bonds tend to deviate from the zero-beta performance, particularly during the 2007-08 financial crisis.

We broaden the extant literature along three dimensions. First, we extend the Durbin-Wu-Hausman [**DWH**] test (Durbin, 1954; Wu, 1973; Hausman, 1978) to a multivariate linear regression [**MLR**] setting with possibly non-Gaussian disturbances. While the univariate DWH test applies in a context of a single regression, our multivariate extension allows to assess the endogeneity of MLR regressors *jointly across equations* with the size accuracy maintained for any sample size and even in the setting with weak instruments. Novel to the literature, our multivariate test could be particularity useful in the context of MLR financial models and for asset pricing tests.

Second, we extend the multivariate instrumental variables [**IV**] test of Dufour, Khalaf and Kichian (2013, JME) by instrumenting factors that remain the same *across equations* which implies that instruments themselves are the same *over the cross section*. The extended method maintains the correct size no matter the number of observations in the sample and even in the presence of weak instruments. While Dufour, Khalaf and Kichian (2013, JME) apply their Wilks-based IV test for inference on dynamic stochastic general equilibrium [**DSGE**] and structural macroeconomic models, the extension that we propose is of particular importance for financial modeling and asset pricing which often proceeds in the multivariate context with the same regressors across equations.

Third, we apply our extended methods to conduct an exact, joint zero-beta analysis of CBMFs taking into account factor endogeneity. In particular, we assess the endogeneity of risk factors jointly (across mutual funds) via the multivariate DWH test and evaluate the joint significance of factor loadings using our extended Wilks-based IV test invariant to endogenous risk factors. The analysis proceeds in the context of the traditional Capital Asset Pricing Model [**CAPM**] with an excess market return (Sharpe, 1964; Lintner, 1965*a*,*b*) and its extended version, the Quadratic CAPM [**QCAPM**], that incorporates market coskewness as a second factor via a mimicking portfolio for the squared market return. The importance of the market coskewness for investors has been widely emphasized and is supported empirically and theoretically in the literature (see, e.g., Kraus and Litzenberger, 1976; Barone-Adesi, 1985; Harvey and Siddique, 2000; Barone-Adesi, Gagliardini and Urga, 2004).

Several empirical results that we obtain are of particular interest. Before the 2007-09 US recession, the joint exogeneity of risk factors is rejected at a 5% level given statistically significant multivariate DWH test. In contrast to the non-instrumented joint test, which yields insignificant factor loadings before the recession, taking into account factor endogeneity produces different results. In particular, our Wilks-based IV test is rejected at the 5% level in the first sub-period suggesting that CBMFs did not perform as zero-beta assets. Before the recession, these findings hold for both CAPM and QCAPM regardless of whether the errors are Gaussian or Student-t. Results are similar in the QCAPM setting during the economic downturn. The null of joint factor exogeneity is also rejected over the full sample with factor betas found to be jointly significant both with and without instrumenting. Our findings overall suggest that the performance of CBMFs tends to diverge from that of zero-beta assets, and attest to the advantages of using the extended methods that we propose.

The remaining sections are assembled as follows. In the subsequent section, we start with the general modeling framework and methodology followed by the outline of the exact, multivariate DWH test and the exact, Wilks-based joint test of a beta significance with and without instrumenting. An empirical analysis of CBMFs is provided in the section 4.3. Summarizing notes are presented in section 4.4.

4.2 Model and Methodology

4.2.1 General Framework

The analysis proceeds in a setting of a general MLR model given by:

$$Y = XB + U, \tag{4.1}$$

partitioned as follows:

$$Y = ZA + HD + U, \tag{4.2}$$

$$X = [Z, H], \quad B = \begin{bmatrix} A \\ D \end{bmatrix},$$

where Y is a $T \times n$ matrix of regressands. Also, X is a $T \times k$ non-singular matrix of regressors with only ones in the first column, which groups together a $T \times g$ matrix H and a $T \times q$ matrix Z (including a column vector of ones) with $k = q + g$. In addition, B gathers n cross-sectional coefficients on k regressors into a $k \times n$ matrix and comprises of a $q \times n$ and $g \times n$ matrices A and D respectively. Further, $U = [U_1, \ldots, U_n] = [\tilde{U}_1, \ldots, \tilde{U}_T]'$ is a $T \times n$ matrix of shocks such that:

$$\tilde{U}_t = LG_t, \quad t = 1, \ldots, T, \tag{4.3}$$

where L is a full-column matrix (not known). With $\mathcal{I}_n$ denoting hereafter an n-dimensional identity matrix, the distribution of G_t either takes the form:

$$G_t \overset{iid}{\sim} \mathcal{N}(0, \mathcal{I}_n), \tag{4.4}$$

or is given by:

$$G_t = C_{1t}/(C_{2t}/\eta)^{1/2}, \quad t = 1, \ \ldots \ , \ T, \tag{4.5}$$

$$C_{1t} \sim N[0, I_n], \quad C_{2t} \sim \chi^2(\eta), \tag{4.6}$$

such that C_{1t} and C_{2t} are independent and η denotes a degrees of freedom parameter.

Building on the above MLR setting, the analysis involves testing a joint statistical significance of regression coefficients in D, which formally relies on the following joint null hypothesis:

$$H_0 : RB = Q, \tag{4.7}$$

where matrix $R = [\mathcal{O}_{g\times q}, \mathcal{I}_g]$ has dimensions $g \times k$ and is assembled to retrieve a matrix of coefficients D from B. Also, $Q = R\bar{B}$ is a $g \times n$ matrix, where $\bar{B}$ denotes a $k \times n$ matrix of known values for its respective counterparts in B. For instance, Q could be equal to $\mathcal{O}_{g\times n}$ that, hereafter, is used to denote a matrix of zeros with dimensions $g \times n$.

Given the Wilks statistic of the form

$$\Psi = \frac{|\hat{U}'\hat{U}|}{|\hat{U}_r'\hat{U}_r|}, \tag{4.8}$$

we test the null hypothesis (4.7) using a monotonically transformed version of Ψ. The latter is a function of residual matrices $\hat{U}$ and $\hat{U}_r$ obtained respectively from the unrestricted and restricted models such that:

$$\hat{U} = Y - X\hat{B} = MY = MU, \quad \hat{U}_r = Y - X\hat{B}_r = Y - Z\hat{A} = M_r Y = M_r U, \tag{4.9}$$

where $\hat{B}_r$ and $\hat{B}$ are OLS estimators of B resulting respectively with and without a parameter restriction. Also, when $Q = \mathcal{O}_{g\times n}$, $\hat{A}$ obtains as an OLS estimator of A in (4.2) imposing the null hypothesis (4.7), that is

$$\begin{aligned} &\hat{B} = (X'X)^{-1}(X'Y), \quad \hat{B}_r = \hat{B} - (X'X)^{-1}R'[R(X'X)^{-1}R']^{-1}R\hat{B}, \\ &\hat{A} = (X'X)^{-1}(X'Y), \end{aligned} \tag{4.10}$$

and

$$\begin{aligned} &M = \mathcal{I}_T - X(X'X)^{-1}X', \\ &M_r = M + X(X'X)^{-1}R'[R(X'X)^{-1}R']^{-1}R(X'X)^{-1}X' = \mathcal{I}_T - Z(Z'Z)^{-1}Z'. \end{aligned} \tag{4.11}$$

In a Gaussian case given by (4.4) and (4.6), testing the null hypothesis (4.7) relies on the following distributional result available in the literature (see Anderson, 1984; Rao, 1973):

$$\begin{aligned} &\left(\frac{\rho\tau - 2\gamma}{gn}\right)\left(\frac{1}{\Psi^{1/\tau}} - 1\right) \sim \mathcal{F}(gn, \rho\tau - 2\gamma), \quad \text{if} \quad min(g,n) \leq 2, \\ &\tau = \begin{cases} [(g^2n^2 - 4)/(g^2 + n^2 - 5)]^{1/2} & \text{if } g^2 + n^2 - 5 > 0, \\ 1 & \text{otherwise}, \end{cases} \\ &\gamma = \frac{gn - 2}{4}, \quad \rho = T - k - \left(\frac{n - g + 1}{2}\right), \end{aligned} \tag{4.12}$$

which is asymptotically valid if $g > 2$ and $n > 2$ (Rao, 1973) and applies exactly for any sample size otherwise.

Further, the result (4.12) nests as a special case the Hotelling statistic that obtains when there are only n parameter restrictions, i.e., $g = 1$:

$$\left(\frac{1}{\Psi} - 1\right)\frac{d}{n} \sim \mathcal{F}(n, d), \quad d = T - n - k + 1. \tag{4.13}$$

In a case with Student-t($\bar{\eta}$) errors as in (4.5) and (4.6), where $\bar{\eta}$ denotes a particular value for η, the Wilks statistic and its monotonically transformed variants in (4.12) and (4.13) have non-standard distributions. To proceed with inference on (4.7) in this setting, we use the distributional result of Dufour and Khalaf (2002, JE), which states that the Wilks statistic and the measure given by

$$\frac{|G'MG|}{|G'M_rG|}, \tag{4.14}$$

have the same null distributions under the assumption (4.3) for the errors.

Since for a particular value $\bar{\eta}$, the distribution of G is fully known in a Student-t($\bar{\eta}$)

setting and given that neither M nor M_r depend on unknown parameters, the Wilks statistics and its monotonically transformed counterparts in (4.12) and (4.13) are pivotal. In this case, we can use the Monte Carlo [**MC**] method of Dwass (1957); Barnard (1963); Dufour (2006) to produce exact p-values for hypothesis testing based on statistics in (4.12) and (4.13). The MC method is restated in the Appendix B.

The multivariate DWH test of exogeneity, test of joint beta significance without IV and its IV-based counterpart arise as special cases of the above general framework and are presented in the following sections.

4.2.2 Exact, joint test without IV

The analysis builds on the following MLR model with n cross-sectional observations and T time periods:

$$y_i = F\beta_i + X_1\theta_i + v_i, \quad i = 1, ..., n, \tag{4.15}$$

where y_i is a $T \times 1$ vector of observations on a regressand i and F collects data on f regressors (*possibly endogenous*) in a $T \times f$ matrix with their respective coefficients grouped together in a $f \times 1$ vector β_i. Also, X_1 is a $T \times k_1$ matrix with observations on exogenous explanatory variables and a unity vector in the first column. Note that X_1 may consist only of a column of ones. Further, the associated coefficients on X_1 are placed into a $k_1 \times 1$ vector θ. Also, v_i is a $T \times 1$ vector of disturbances for an observation i.

In this setting, the joint hypothesis of interest involves cross-sectional coefficients on all regressors in F and is formally given by:

$$H_{01} : \beta_i = \bar{\beta}_i, \quad \bar{\beta}_i, \ \textit{is known}, \ i = 1, ..., n, \tag{4.16}$$

where $\bar{\beta}_i$ is a $f \times 1$ vector of known values for the respective parameters in β_i.

To proceed with the hypothesis testing, consider restating expressions (4.15) and (4.16) as in (4.1), (4.2) and (4.7). This requires gathering observations as follows. Group together data on endogenous variables into a $T \times n$ matrix $Y = [y_1, ..., y_n]$. Setting $g = f$ and $q = k_1$, let $H = F$ and $Z = X_1$ collect time series on regressors respectively into a $T \times g$ and $T \times q$ matrices. These could be further assembled into a $T \times k$ matrix $X = [Z, H]$ with $k = q + g$. Also, gather coefficients so that $D = [\beta_1, ..., \beta_n]$ is a $g \times n$ matrix and $A = [\theta_1, ..., \theta_n]$ is a $q \times n$ matrix so that

$$B = \begin{bmatrix} A \\ D \end{bmatrix} = \begin{bmatrix} \theta_1, ..., \theta_n \\ \beta_1, ..., \beta_n \end{bmatrix}, \tag{4.17}$$

with the associated $k \times n$ matrix $\bar{B}$ of fixed values for B. Further, group together disturbances into a $T \times n$ matrix $U = [v_1, ..., v_n]$.

Given the above mapping into a general case, we can test (4.16) by applying the distributional result in (4.12) and (4.13) when the errors are Gaussian or by using an exact, MC p-values simulated in a Student-t($\bar{\eta}$) setting as described in the previous section given (4.14).

4.2.3 Exact, multivariate Durbin-Wu-Hausman-type Test

We extend the DWH test to a *multivariate* setting given by (4.15) with possibly non-Gaussian disturbances to evaluate exogeneity of explanatory variables in F *jointly*. The extended DWH test is *size-correct* whatever the number of sample observations, and involves the two steps below:

1. Given a $T \times k_2$ matrix X_2 of k_2 instruments, obtain a $T \times f$ matrix of residuals, $\hat{\epsilon}$, by regressing F on X_1 and X_2.

2. Plug in the residuals from step 1 into the following model:
$$y_i = X_1 a_i + F\delta_i + \hat{\epsilon}\lambda_i + u_i, \quad i = 1, \ldots , n, \tag{4.18}$$
where λ_i is a $f \times 1$ vector of loadings on residuals, while coefficients on X_1 and F are gathered respectively into $k_1 \times 1$ and $f \times 1$ vectors a_i and δ_i. Also, u_i denotes a $T \times 1$ vector of errors for a regressand i.

Given equation (4.18), the multivariate DWH test is defined for the following joint null hypothesis of exogeneity:
$$H_{02} : \lambda_i = \mathcal{O}_{f\times 1}, \quad i = 1, \ldots , n. \tag{4.19}$$
Expressions (4.1), (4.2) and (4.7) provide a more general way to state (4.18) and (4.19). This involves collecting dependent variables in (4.18) into a $T \times n$ matrix $Y = [y_1, ..., y_n]$ and grouping together regressors and their respective coefficients respectively into a $T \times k$ and $k \times n$ matrices X and B given by
$$X = [Z, H], \quad B = \begin{bmatrix} A \\ D \end{bmatrix}, \quad A = \begin{bmatrix} a_1, ..., a_n \\ \delta_1, ..., \delta_n \end{bmatrix}, \quad D = [\lambda_1, ..., \lambda_n],$$
where the mapping in terms of dimensions is given by $k = q + g$, $g = f$ and $q = k_1 + g$. Also, $Z = [X_1, F]$ is a $T \times q$ matrix of regressors and $H = \hat{\epsilon}$ is a $T \times g$ matrix of residuals. Further, A and D are respectively $q \times n$ and $g \times n$ coefficient matrices. In addition, $Q = \mathcal{O}_{g\times n}$.

Given the above correspondence with the general case, the multivariate DWH test proceeds further as follows. The null hypothesis (4.19), stated in its general form as in (4.7), can be assessed using the Fisher-distributed Wilks-based statistics in (4.12) and (4.13) provided that errors are Gaussian as in (4.3) and (4.4).

In a Student-t($\bar{\eta}$) setting, the distributions of the Wilks statistic and its monotonically transformed counterparts in (4.12) and (4.13) remain invariant to unknown parameters but are non-standard. In this case, the hypothesis testing relies on the distributional equivalence between the Wilks statistic and the criteria given by (4.14) (Dufour and Khalaf, 2002). In particular, the latter measure can be used to simulate exact, MC p-values to proceed with the inference on (4.19).

4.2.4 Exact, joint IV test

Consider the MLR setting given by (4.15) and let all regressors in F be endogenous. To test the joint null hypothesis (4.16) taking the endogeneity into account, we extend the multivariate, Wilks-based IV test of Dufour, Khalaf and Kichian (2013, JME) used for inference on DSGE and structural macroeconomic models. While similar to the latter test in terms of a reliance on an auxiliary IV-based regression, the extension that we propose is distinct as it involves the same instruments across equations.

In particular, given a $T \times k_2$ matrix of instruments X_2, the extended joint IV test builds on the following supplementary regression:

$$y_i - F\bar{\beta}_i = X_1\psi_i + X_2\phi_i + w_i, \quad i = 1, \ldots, n, \tag{4.20}$$

where ψ_i and ϕ_i are respectively $k_1 \times 1$ and $k_2 \times 1$ vectors of loadings on X_1 and X_2, while $\bar{\beta}_i$ is a $f \times 1$ vector of fixed values that are being tested for the respective parameters in β_i. Also, w_i is a $T \times 1$ vector of errors.

Given (4.20), the extended joint IV test is defined for the following auxiliary null hypothesis:

$$H_{03} : \phi_i = \mathcal{O}_{k_2 \times 1}, \quad i = 1, \ldots, n, \tag{4.21}$$

with a significant α-level test indicating a rejection of both the auxiliary restriction in (4.21) and the hypothesis of interest in (4.16).

Going from expressions (4.20) and (4.21) to a more general setting given by (4.1), (4.2) and (4.7) requires grouping the variables and coefficients as follows. Let $\tilde{y}_i = y_i - F\bar{\beta}_i$, $i = 1, ...n$, and assemble dependent variables into a $T \times n$ matrix $Y = [\tilde{y}_1, ..., \tilde{y}_n]$. Setting $q = k_1$ and $g = k_2$, let $Z = X_1$ and $H = X_2$ with the corresponding coefficients assembled into a $k_1 \times n$ and $k_2 \times n$ matrices $A = [\psi_1, ..., \psi_n]$ and $D = [\phi_1, ..., \phi_n]$ respectively. Also, let $U = [w_1, ..., w_n]$ collect error terms into a $T \times n$ matrix and let $Q = \mathcal{O}_{g\times n}$.

Using the above general notation, we can restate the the null hypothesis (4.21) as in (4.7) and test it in a Gaussian setting using the Wilks-based results in (4.12) or (4.13). In the Student-t($\bar{\eta}$) case, the inference proceeds given the distributional equivalence between the criteria in (4.14) and the Wilks statistic (Dufour and Khalaf, 2002), since the distribution of the latter and its variants in (4.12) and (4.13), while remain pivotal, are no longer standard. Given that pivotality under Student-t($\bar{\eta}$) errors is retained, we can employ the MC method to calculate exact p-values for tests involving Wilks-based statistics in (4.12) and (4.13) by drawing on their distributional link with the measure in (4.14).

4.3 An empirical analysis of CBMFs

We apply the joint test without IV, IV-based joint test and the multivariate DWH test presented in sections 4.2.1-4.2.4 to test whether CBMFs are zero-beta assets taking into account the factor endogeneity. The analysis proceeds in the context of the MLR model (4.15) with y_i denoting excess returns (less the risk-less rate) on CBMFs, X_1 given by a $T \times 1$ vector of ones and F collecting observations on the risk factors. The zero-beta analysis involves testing the joint statistical significance of all factor loadings which is formally given by the following joint null hypothesis:

$$H_{01} : \beta_i = \mathcal{O}_{f\times n}, \quad i = 1, ..., n, \tag{4.22}$$

In particular, whether CBMFs are zero-beta is assessed against two benchmarks including the single-factor CAPM-based model with an excess (over the risk-free rate) market return. In addition, we also consider the QCAPM that augments the excess market return with a mimicking return for its square to account for the market coskewness (see, e.g., Kraus and Litzenberger, 1976; Barone-Adesi, 1985; Barone-Adesi, Gagliardini and Urga, 2004).

In assessing CBMFs against financial benchmarks, the factor endogeneity problem can arise for two reasons. First, given that estimates from a regression of a non-tradable factor on base assets are typically used in generating mimicking returns, the latter are estimated with an error. As a result, replacing the squared market return with its mimicking return in the QCAPM-based setting can introduce a measurement error leading to spurious inference on factor betas (see, e.g., Kleibergen and Zhan, 2018).

Second, risk factors can be endogenous due to the omitted-variable bias. In particular, the analysis of CBMFs in the preceding chapters have focused on systematic risk factors as is common in the asset pricing literature, which argues that idiosyncratic risks are diversifyable and, thus, need not be compensated through excess expected return. With their performance contingent on natural catastrophes, CBMFs are not like traditional financial assets. As such, other factors, besides those that capture systematic risks, may be relevant for the pricing of CBMFs. In this regard, existing literature provides evidence on the importance of a price for traditional reinsurance and size at issuance, credit rating and trigger variable of Catastrophe bonds for their valuation (see, e.g., Gürtler, Hibbeln and Winkelvos, 2014; Braun, 2015).

In the context of assessing CBMFs, it may be relevant to consider their assets under management (AUM), composition in terms of credit rating and triggers of the underlying Catastrophe bonds and the cost of traditional reinsurance. Due to limited publicly available data on these variables or the frequency at which this data is available, these factors cannot be incorporated in the current analysis.

Omitting these variables can lead to the endogeneity problem as they could be related to financial market benchmarks. In particular, there could be linkages between the state of financial markets and these variables. For instance, in the low interest rate environment investors "reaching for the yield" may find CBMFs that offer attractive returns more appealing which could be reflected in their larger AUM if higher demand is matched on the supply side. Investors may be also more interested in CBMFs with a riskier composition (in terms of credit ratings and triggers of underlying Catastrophe bonds) in the environment with generally low interest rates on traditional assets. Developments in financial markets may be also linked to the price of traditional reinsurance as the latter is provided by reinsurance companies that are subject to systematic risks. As such, it is important to test for and take into account factor endogeneity when assessing the dynamics between CBMFs and financial markets.

As instruments for the excess market return and the mimicking portfolio for its square, we use the lagged growth in the S&P/Case-Shiller U.S. National Home Price Index and the lagged growth in the US Economic Policy Uncertainty Index developed by Baker, Bloom and Davis (2016). Given that developments in the US housing market do not cause natural disasters, nationwide housing market in the US is likely to affect CBMFs only indirectly through financial markets. This validates the lagged US housing price inflation as an instrument satisfying the exclusion restriction. In particular, CBMFs could be exposed to financial markets via the collateral and financial counterparties of the Catastrophe bonds that these funds hold in their portfolio. Thus, a housing market shock that severely affects financial markets could transmit indirectly to CBMFs. For instance, until the collapse of the US housing market and the ensuing 2007-08 financial crisis, it was common for Catastrophe bonds to hold as collateral complex investments like mortgage-backed securities (MBS) tied to the US housing loans. When the US housing market crashed causing a global financial meltdown, several Catastrophe bonds defaulted due to severe repricing of their collateral assets with the impact further amplified by the bankruptcy of their key financial counterparty, Lehman Brothers. In addition, given that the US housing price growth is based on the nationwide index, its fist lag is a valid instrument also because any links between the housing market and natural disasters at the regional level in the US are likely to be averaged out at the national level. To further reinforce the above arguments, it is also worth noting that CBMFs include Catastrophe bonds covering catastrophes in regions outside of the US that are not linked to the US housing market.

In terms of the instrument based on the US economic policy uncertainty, the latter does not cause natural disasters that may be covered by Catastrophe bonds and as such have no direct influence on CBMFs. Hence, this variable does not belong in the model for CBMFs directly. However, the importance of the economic policy uncertainty for financial markets has been documented empirically (see, e.g., Sum, 2012; Fang, Chen, Yu and Qian, 2017; Asgharian, Christiansen and Hou, 2018). Given that CBMFs may be exposed to financial markets via the structure of the Catastrophe bonds that are in funds' possession (e.g., collateral, counterparties), the ambiguity shock about economic policy developments could transmit to CBMFs indirectly via financial markets. In light of the above, we model CBMFs with the lagged growth for the US economic policy uncertainty index used as an instrument for the mimicking portfolio on the squared market return in the QCAPM setting.

4.3.1 Data

For our empirical investigation, we use data between 11/2004 and 12/2015 and provide results over the entire period as well as for the following three sub-samples covering respectively periods before, during and after the 2007-09 US recession: 11/2004 - 11/2007, 12/2007 - 06/2009, 07/2009 - 12/2015.[2]

The analysis relies on CBMFs listed in the Table 4.1. Returns on CBMFs are constructed as a first difference of the logarithmically transformed fund prices retrieved from Bloomberg. Before computing returns, fund prices were converted into USD based on the exchange rates for Euro (DEXUSEU) and Swiss Frank (DEXSZUS) obtained from the website for the Federal Reserve Economic Data (FRED). To model CBMFs, we use their excess returns expressed in deviation from the risk-free rate. The latter is given by the one-month Treasury Bill rate from the Wharton Research Data Services (WRDS). Figures 4.1-4.2 display excess returns on CBMFs graphed over the entire study period.

As a market factor, we use the return on the value-weighted portfolio comprising of all equities listed on the NYSE, AMEX and Nasdaq (variable VWRETD) obtained from the Center for Research in Security Prices (CRSP). In the analysis, we use the excess market return net of the risk-free rate (same as for CBMFs).

For the QCAPM-based regression, we also construct a mimicking portfolio for the squared market return as a weighted combination of the base asset returns. The latter are given by the US Treasury 10-year government bond yield (variable USGG10YR) from Bloomberg, the momentum factor and returns on six Fama-French stock portfolios sorted on size and book-to-market from the online Kenneth French Data Library. The procedure for the portfolio construction is described in the Appendix C.

Our instruments are based on the S&P/Case-Shiller U.S. National Home Price Index (variable CSUSHPINSA) and the US Economic Policy Uncertainty Index of Baker, Bloom and Davis (2016) (variable USEPUINDXD), both retreived from the Federal Reserve Economic Data (FRED). For the analysis, we use the first difference of the logarithmically transformed time series for each variable, lagged by one period back.

[2] The division into sub-periods is based on dates from the National Bureau of Economic Research.

4.3.2 Summary statistics

In this section, we examine sample moments estimated for excess returns on CBMFs, risk factors and instruments used in the analysis.

Estimates for sample mean, variance, skewness and kurtosis are provided in the Table 4.2. In terms of full-sample estimates, excess returns for most CBMFs have positive means and a similar degree of volatility but differ based on skewness and kurtosis. Over time, simple moments change considerably for CBMFs. While all positive before the recession, mean excess fund returns turn almost all negative during the downturn, recovering somewhat in the following sub-period. Volatility of returns on CBMFs is also the highest during the period of economic turmoil. In sub-samples, CBMFs remain dispersed in terms of their skewness and kurtosis and retain some similarity in terms of means and variance, although less so during the recession.

The excess market return and the mimicking portfolio for its square display positive means in all periods except during the recession and have similar kurtosis estimates in every case. Both risk factors also have higher variances at the time of the downturn than in any other period.

The lagged US house price growth is positive on average during both tranquil sub-periods, but becomes negative during the economic slowdown. Over time, volatility of the lagged US house price inflation rises. This instrument displays modest degree of skewness and kurtosis across periods. The lagged growth in the US economic policy uncertainty has positive mean in all cases except after the recession. In all periods, this variable varies the most in our dataset and is moderate in terms of excess skewness and kurtosis.

Correlations estimated between variables are displayed in the Table 4.3. Except for two funds inversely related to each other during the recession, in all other cases we observe positive relationship between all pairings of CBMFs. Excess market return comoves positively with excess returns on all CBMFs in every period with correlations rising across funds between the first two sub-samples. Relationship of CBMFs with the mimicking portfolio for the squared market return is mostly positive and becomes more pronounced for most funds during the recession. The lagged US house price growth correlates mostly negatively with CBMFs over the whole sample and in every sub-period except during the downturn. For the lagged growth in US economic policy, its dynamics with mutual funds switches from mostly positive during the initial tranquil sub-period to negative as the recession gains momentum.

4.3.3 MLR results

Regression results based on CAPM and QCAPM obtained in a Gaussian setting are reported in the Table 4.4. The analysis provides evidence against the joint exogeneity of risk factors. In particular, both in the CAPM and QCAPM cases, the multivariate DWH test is statistically significant at the 5% level before the 2007-09 recession. For the QCAPM-based regression, the joint null hypothesis of factor exogeneity is also rejected at the 10% level during the economic downturn and over the full sample. The difference between the results from the Wilks-based test of a joint beta significance obtained with and without instrumenting further highlights the importance of using the method robust to the factor endogeneity for the analysis. In particular, while the IV-based test is statistically significant at the 5% level in the first sub-period for both the CAPM and QCAPM, its counterpart without IV yields jointly insignificant factor betas. The same result obtains for the QCAPM-based regression in the recession sub-period. Both with and without instrumenting, the null hypothesis of factor loadings being jointly close to zero is rejected at the 10% level over the full sample. Taking endogeneity into account, our Gaussian-based findings overall suggest that CBMFs do not always perform as zero-beta assets.

Similar trends emerge based on the MLR results obtained under Student-t(η) errors. Tables 4.5 and 4.6 display exact MC p-values simulated respectively in the CAPM and QCAPM setting. In line with Gaussian-based results, the multivariate DWH test is rejected at the 5% level across all degrees of freedom before the recession for both the CAPM and QCAPM. In terms of a joint beta significance, test results vary for both CAPM and QCAPM in the first period depending on whether endogeneity is taken into account or not. Unlike its non-instrumented analog, the IV-based joint test is significant at the 5% level for all values of η pre-recession. Similar results are obtained for the QCAPM during the recession period. To that end, both the multivariate DWH test and the Wilks-based IV tests are significant at the 10% and 5% levels respectively for any value of η, while insignificant betas result based on the joint test without IV. Over the full-sample, QCAPM-based analysis in the Student-t(η) setting also provides evidence against joint factor exogeneity and reveals jointly significant factor loadings with and without IV. Taken together, results from the Student-t(η) case reinforce Gaussian-based evidence suggesting that the performance of CBMFs is not always consistent with that of zero-beta assets.

4.4 Conclusion

In this paper, we propose a multivariate version of the univariate DWH test (Durbin, 1954; Wu, 1973; Hausman, 1978) and extend the joint Wilks-based IV test of Dufour, Khalaf and Kichian (2013, JME) to a setting with instruments that remain the same across equations. Both extended tests maintain size control irrespective of how large is the sample, are robust to weak instruments and valid in Gaussian and Student-t(η) settings.

The extended tests are applied to formally examine whether CBMFs are zero-beta investments taking into account the factor endogeneity. For both CAPM and QCAPM, we find empirical evidence against joint factor exogeneity in some cases. These results are robust across distributional settings. In terms of a joint beta significance, the results differ when the endogeneity is taken into account. Unlike its non-instrumented version, the extended IV-based test yields betas that are jointly statistically significant before the 2007-09 US recession both for CAPM and QCAPM benchmarks. This occurs both in Gaussian and Student-t(η) settings. For QCAPM, the same result arises during the recession. Full-sample analysis provides further evidence against joint factor exogeneity in the QCAPM setting. Over the long-run, we also find jointly significant QCAPM factor betas using the extended Wilks-based test with and without IV. Our empirical findings overall suggests that CBMFs do not consistently perform as zero-beta assets.

Figure 4.1: Excess returns on CBMFs between 11/2004 − 12/2015 (Panel A)

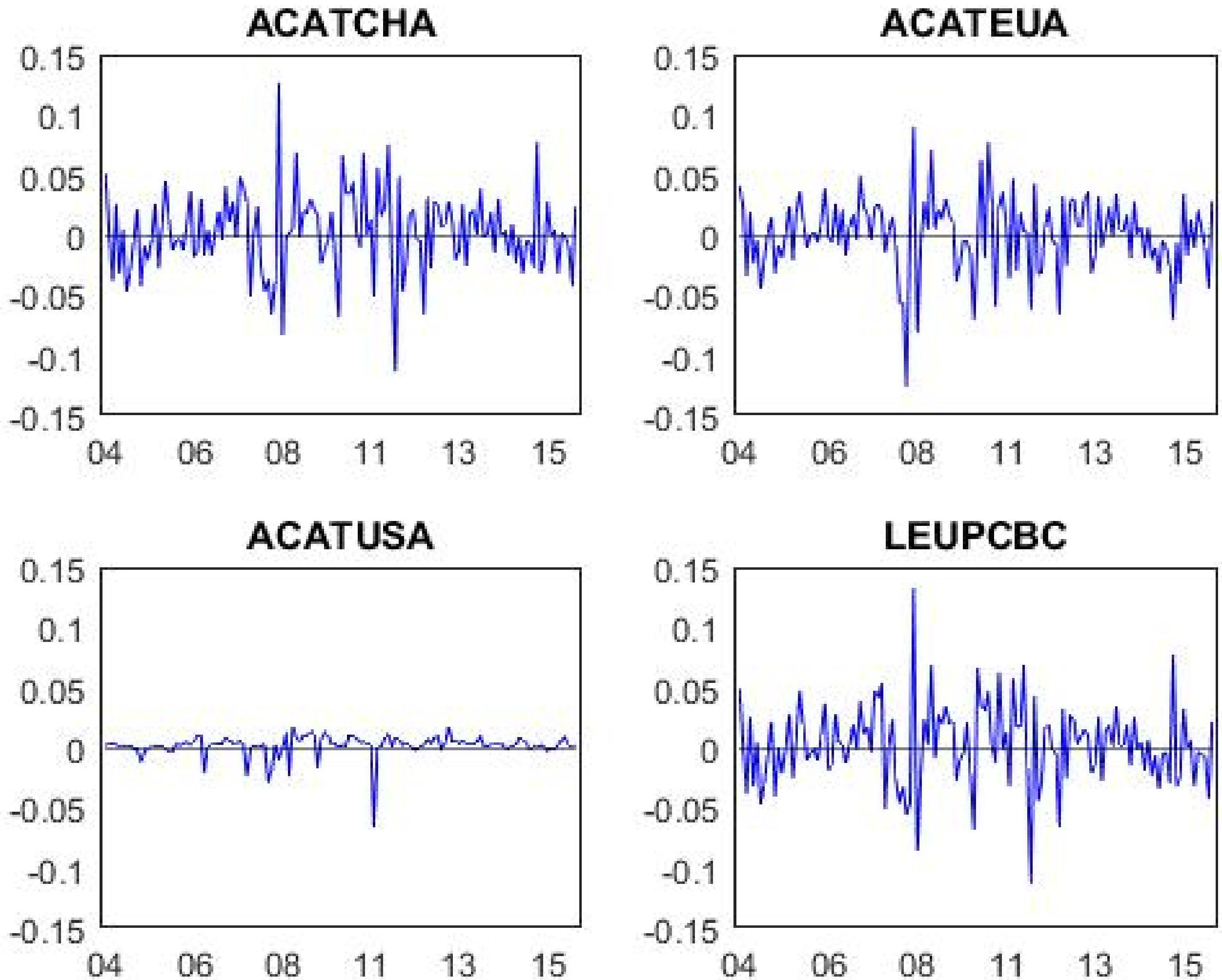
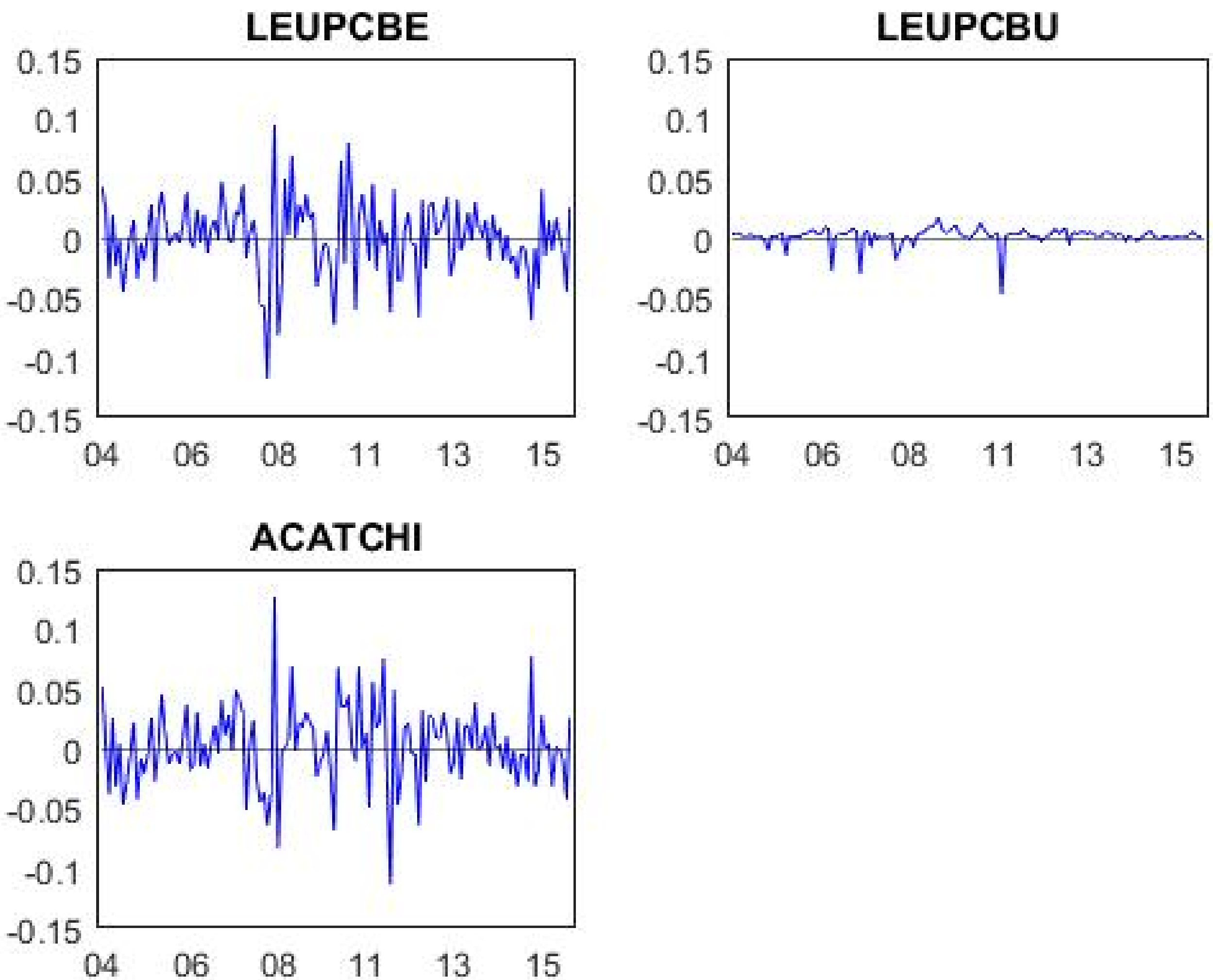


Figure 4.2: Excess returns on CBMFs between 11/2004 − 12/2015 (Panel B)



Tables

Table 4.1: List of mutual funds

#	Bloomberg Ticker	Fund Name
1	ACATCHA	Falcon Cat Bond Fund Class A CHF
2	ACATEUA	Falcon Cat Bond Fund Class A EUR
3	ACATUSA	Falcon Cat Bond Fund Class A USD
4	ACATCHI	Falcon Cat Bond Fund Class I CHF
5	LEUPCBC	LGT CH Cat Bond Fund (CHF) A
6	LEUPCBE	LGT CH Cat Bond Fund (EUR) A
7	LEUPCBU	LGT CH Cat Bond Fund (USD) A

Table 4.2: Descriptive statistics

#	Var	11/2004 - 11/2007				12/2007 - 06/2009				07/2009 - 12/2015				11/2004 - 12/2015			
		Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt	Avr	St Dev	Skew	Kurt
1	*acatcha*	0.000	0.024	0.12	2.37	-0.001	0.049	0.62	3.38	0.003	0.032	-0.43	4.44	0.002	0.033	0.04	4.56
2	*acateua*	0.004	0.021	-0.07	2.57	-0.003	0.048	-0.61	3.70	-0.001	0.030	-0.22	3.06	0.000	0.031	-0.55	4.81
3	*acateusa*	0.001	0.005	-2.05	9.50	-0.002	0.012	-0.79	2.71	0.003	0.009	-5.39	41.12	0.002	0.009	-3.81	26.17
4	*leupcbc*	0.001	0.024	0.01	2.50	0.001	0.051	0.65	3.24	0.003	0.031	-0.46	4.51	0.002	0.033	0.10	4.84
5	*leupcbe*	0.004	0.022	-0.16	2.63	-0.003	0.050	-0.33	3.03	-0.001	0.030	-0.17	3.14	0.000	0.032	-0.38	4.32
6	*leupcbu*	0.000	0.008	-2.63	9.57	0.000	0.006	-1.33	4.18	0.002	0.007	-5.00	39.35	0.001	0.007	-3.62	21.89
7	*acatchi*	0.000	0.024	0.14	2.39	0.000	0.049	0.61	3.35	0.004	0.032	-0.43	4.49	0.002	0.033	0.04	4.58
8	Mkt	0.007	0.025	-0.43	2.29	-0.020	0.072	-0.23	2.67	0.012	0.039	-0.14	3.06	0.006	0.044	-0.77	5.24
9	Mkt^2_{mim}	0.015	0.018	0.31	2.57	-0.018	0.043	-0.23	2.38	0.011	0.023	-0.40	3.17	0.008	0.028	-1.03	5.13
10	$G_{housing}$	0.000	0.007	0.34	1.94	-0.011	0.008	0.59	2.98	0.002	0.009	0.10	2.26	0.000	0.009	0.03	2.48
11	U_{policy}	0.019	0.672	0.24	1.87	0.013	0.591	1.27	5.90	-0.007	0.639	-0.17	3.13	0.003	0.642	0.12	3.03

Table 4.3: Descriptive statistics - correlations

Before Recession: 11/2004 - 11/2007

#	Var	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	Mkt	$Mkt2_{mim}$	$G_{housing}$	U_{policy}
1	*acatcha*	1										
2	*acateua*	0.95	1									
3	*acateusa*	0.28	0.31	1								
4	*leupcbc*	0.99	0.94	0.15	1							
5	*leupcbe*	0.93	0.98	0.26	0.93	1						
6	*leupcbu*	0.13	0.18	0.62	0.09	0.29	1					
7	*acatchi*	1.00	0.95	0.28	0.98	0.92	0.12	1				
8	Mkt	0.06	0.17	0.08	0.07	0.23	0.31	0.05	1			
9	Mkt^2_{mim}	0.05	0.19	0.09	0.05	0.20	0.16	0.06	0.56	1		
10	$G_{housing}$	-0.31	-0.38	-0.27	-0.30	-0.33	0.08	-0.31	0.05	-0.05	1	
11	U_{policy}	0.30	0.23	0.14	0.27	0.22	0.09	0.30	0.08	0.07	-0.01	1

During Recession: 12/2007 - 06/2009

#	Var	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	Mkt	Mkt^2_{mim}	$G_{housing}$	U_{policy}
1	*acatcha*	1										
2	*acateua*	0.88	1									
3	*acateusa*	0.13	0.25	1								
4	*leupcbc*	0.98	0.86	-0.02	1							
5	*leupcbe*	0.87	0.98	0.10	0.88	1						
6	*leupcbu*	0.32	0.47	0.48	0.31	0.51	1					
7	*acatchi*	1.00	0.88	0.12	0.98	0.87	0.32	1				
8	Mkt	0.37	0.59	0.27	0.40	0.63	0.59	0.37	1			
9	Mkt^2_{mim}	0.20	0.37	0.01	0.21	0.39	0.31	0.19	0.44	1		
10	$G_{housing}$	0.11	0.21	0.21	0.10	0.22	0.43	0.11	0.39	0.56	1	
11	U_{policy}	0.00	-0.38	-0.33	0.04	-0.34	-0.42	-0.01	-0.41	-0.22	-0.12	1

After Recession: 07/2009 - 12/2015

#	Var	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	Mkt	$Mkt2_{mim}$	$G_{housing}$	U_{policy}
1	*acatcha*	1										
2	*acateua*	0.65	1									
3	*acateusa*	0.24	0.22	1								
4	*leupcbc*	0.99	0.65	0.17	1							
5	*leupcbe*	0.63	0.99	0.13	0.64	1						
6	*leupcbu*	0.20	0.23	0.91	0.16	0.19	1					
7	*acatchi*	1.00	0.65	0.24	0.99	0.63	0.20	1				
8	Mkt	0.39	0.56	0.02	0.40	0.57	0.10	0.38	1			
9	Mkt^2_{mim}	0.09	0.22	-0.07	0.10	0.23	0.02	0.08	0.50	1		
10	$G_{housing}$	-0.01	-0.02	0.10	-0.02	-0.03	0.06	0.00	-0.26	-0.05	1	
11	U_{policy}	0.18	-0.05	0.05	0.18	-0.04	0.03	0.18	-0.10	-0.02	0.07	1

Full Sample: 11/2004 - 12/2015

#	Var	acatcha	acateua	acatusa	leupcbc	leupcbe	leupcbu	acatchi	Mkt	Mkt^2_{mim}	$G_{housing}$	U_{policy}
1	*acatcha*	1										
2	*acateua*	0.76	1									
3	*acateusa*	0.22	0.23	1								
4	*leupcbc*	0.99	0.76	0.11	1							
5	*leupcbe*	0.74	0.98	0.14	0.76	1						
6	*leupcbu*	0.20	0.25	0.73	0.17	0.26	1					
7	*acatchi*	1.00	0.76	0.21	0.99	0.74	0.20	1				
8	Mkt	0.34	0.52	0.15	0.35	0.54	0.26	0.33	1			
9	Mkt^2_{mim}	0.12	0.27	0.04	0.13	0.28	0.13	0.12	0.52	1		
10	$G_{housing}$	-0.01	-0.01	0.15	-0.03	-0.01	0.15	-0.01	0.07	0.24	1	
11	U_{policy}	0.16	-0.06	-0.01	0.16	-0.05	0.00	0.16	-0.13	-0.04	0.02	1

Note: Estimates for excess returns (net of riskless rate) on CBMFs are listed in the first seven rows. Mkt and Mkt^2_{mim} are respectively the excess market return and the mimicking portfolio for its square. $G_{housing}$ and U_{policy} denote lagged growth in respectively the US home price index and the US economic policy uncertainty.

Table 4.4: CAPM & QCAPM in a Gaussian setting

Period	CAPM			QCAPM		
	DWH	**IV**	**no-IV**	**DWH**	**IV**	**no-IV**
11/2004 - 11/2007	**3.50***	**3.43***	1.41	**2.13***	**2.04***	1.14
12/2007 - 06/2009	0.35	0.46	**4.06***	**2.02****	**2.57***	1.53
07/2009 - 08/2014	0.44	0.43	**5.93***	0.82	0.73	**3.28***
11/2004 - 08/2014	0.89	0.92	**9.19***	**1.66****	**1.62****	**4.40***

Note: *, ** respectively indicate rejection of a joint null hypothesis at 5% and 10% level. Reported values are the estimates of statistics for the DWH test (DWH), joint Wilks-based test with IV (IV) and without IV (no-IV).

Table 4.5: CAPM in a Student-t(η) setting

	11/2004 - 11/2007			**12/2007 - 06/2009**			**07/2009 - 12/2015**			**11/2004 - 12/2015**		
η	**DWH**	**IV**	**no-IV**	**DWH**	**IV**	**no-IV**	**DWH**	**IV**	**no-IV**	**DWH**	**IV**	**no-IV**
2	**0.007**	**0.006**	0.251	0.907	0.831	**0.015**	0.873	0.882	**0.001**	0.526	0.501	**0.001**
3	**0.006**	**0.005**	0.223	0.911	0.842	**0.026**	0.865	0.882	**0.001**	0.540	0.516	**0.001**
4	**0.005**	**0.006**	0.235	0.912	0.852	**0.014**	0.854	0.865	**0.001**	0.526	0.506	**0.001**
5	**0.013**	**0.012**	0.238	0.902	0.836	**0.023**	0.880	0.873	**0.001**	0.525	0.494	**0.001**
6	**0.012**	**0.012**	0.233	0.896	0.841	**0.026**	0.865	0.868	**0.001**	0.539	0.519	**0.001**
7	**0.007**	**0.007**	0.234	0.908	0.865	**0.026**	0.872	0.878	**0.001**	0.520	0.511	**0.001**
8	**0.008**	**0.011**	0.229	0.904	0.835	**0.026**	0.880	0.881	**0.001**	0.511	0.486	**0.001**
9	**0.005**	**0.005**	0.223	0.906	0.846	**0.021**	0.867	0.876	**0.001**	0.497	0.477	**0.001**
10	**0.010**	**0.010**	0.217	0.899	0.840	**0.027**	0.865	0.869	**0.001**	0.518	0.495	**0.001**
100	**0.007**	**0.008**	0.232	0.898	0.841	**0.020**	0.871	0.878	**0.001**	0.526	0.494	**0.001**

Table 4.6: QCAPM in a Student-t(η) setting

	11/2004 - 11/2007			**12/2007 - 06/2009**			**07/2009 - 12/2015**			**11/2004 - 12/2015**		
η	**DWH**	**IV**	**no-IV**	**DWH**	**IV**	**no-IV**	**DWH**	**IV**	**no-IV**	**DWH**	**IV**	**no-IV**
2	**0.020**	**0.022**	0.335	**0.096**	**0.036**	0.189	0.644	0.766	**0.001**	**0.056**	**0.072**	**0.001**
3	**0.019**	**0.022**	0.338	**0.098**	**0.039**	0.208	0.622	0.744	**0.001**	**0.071**	**0.073**	**0.001**
4	**0.019**	**0.023**	0.347	**0.097**	**0.042**	0.194	0.63	0.745	**0.001**	**0.064**	**0.078**	**0.001**
5	**0.023**	**0.031**	0.339	**0.091**	**0.029**	0.184	0.639	0.756	**0.001**	**0.063**	**0.080**	**0.001**
6	**0.026**	**0.032**	0.349	**0.106**	**0.029**	0.183	0.656	0.733	**0.001**	**0.069**	**0.075**	**0.001**
7	**0.016**	**0.022**	0.353	**0.085**	**0.035**	0.175	0.659	0.752	**0.002**	**0.071**	**0.079**	**0.001**
8	**0.016**	**0.027**	0.336	**0.093**	**0.026**	0.197	0.645	0.758	**0.001**	**0.061**	**0.077**	**0.001**
9	**0.020**	**0.022**	0.347	**0.078**	**0.032**	0.176	0.657	0.749	**0.002**	**0.070**	**0.076**	**0.001**
10	**0.026**	**0.022**	0.339	**0.092**	**0.031**	0.179	0.639	0.754	**0.001**	**0.058**	**0.077**	**0.001**
100	**0.020**	**0.027**	0.342	**0.089**	**0.031**	0.184	0.631	0.747	**0.001**	**0.069**	**0.086**	**0.001**

Note: Tables 5 and 6 report estimates of exact, MC p-values for the DWH test (DWH), joint Wilks-based test with IV (IV) and without IV (no-IV). η indicates the value of the degrees of freedom parameter.

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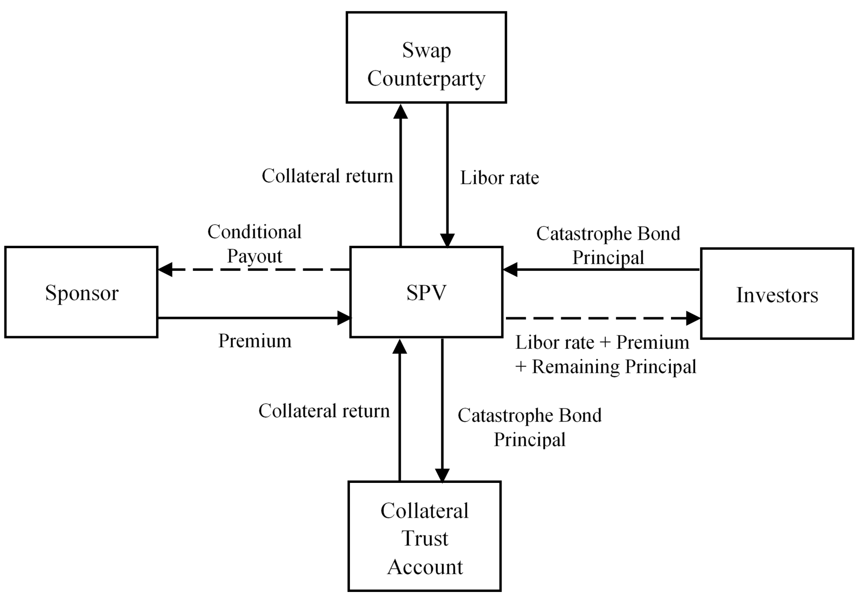
Appendices 4

A Catastrophe Bonds

Alternative to traditional reinsurance, Catastrophe bonds allow reinsurers or national governments to raise funds in a timely manner in the event of a large-scale catastrophe, like tornado or earthquake, to pay out policy claims or support the disaster relief and recovery efforts. Although fairly new, the market for Catastrophe bonds has expanded considerably since its inception two decades ago attracting US $30 billion in outstanding capital from investors in 2017 (Artemis, 2017). Vital for reinsurance markets, these bonds provide nearly 30% of the worldwide alternative funding for protection against the catastrophe risk (Aon Benfield, 2017a).

As shown in the Figure 4.A.1, a Catastrophe bond is usually structured with a Special Purpose Vehicle (SPV) that, through an agreement, takes over a risk of incurring a loss due to a triggering peril from a sponsor that issues the bond. The SPV then redistributes the accepted catastrophe risk across investors in financial markets through a sale of Catastrophe bonds with proceeds kept in the form of collateral assets that consist of highly-rated financial securities. Bond buyers are promised payouts in the form of a principal on the maturity date and regular coupons (premium and a floating rate, like Libor) until the bond expires. In the event of a default-triggering catastrophe, the sponsoring party receives funds raised through the sale of collateral assets with bond holders losing a portion of or possibly even all their remaining payouts. Until the 2007-08 financial crisis, most Catastrophe bonds also relied on

Figure 4.A.1: Catastrophe bond transaction



a Total Return Swap Counterparty (TRSC) to guard against the interest rate and collateral value risks. Given the mid-crisis default of several Catastrophe bonds due to their severely impaired collateral assets with the impact further compounded by the collapse of their TRSC, the Lehman Brothers, the use of the TRSC has for the most part been replaced with other measures. In particular, securities acceptable as collateral have been limited to safe, transparent and risk-free investments like US Treasuries. Post-crisis provisions also require that the collateral account is constantly monitored and involve systematic updates to investors.

B Monte Carlo Method

The MC method due to Dwass (1957); Barnard (1963); Dufour (2006) is summarized below.

Given the MLR setting in (4.1)-(4.3) and imposing the null hypothesis of interest, suppose the following transformation of a test statistic $\Pi(Y, X)$ exist

$$\Pi(Y, X) = \tilde{\Pi}(G, X)$$

where X is a matrix of regressors and G is distributed as in (4.4) or (4.5)-(4.6) where the η parameter is fixed.

With $\Pi^{(0)}$ denoting the estimated statistic given the observed sample, an exact p-value for Π, $\hat{p}_K[\Pi] = p_K[\Pi^{(0)}, \Pi]$, then obtains as follows:

$$p_K[c, \Pi] \equiv (1+K)^{-1}\left(1 + \sum_{j=1}^{K} I_+\left[\Pi^{(j)} - c\right]\right), \tag{B1}$$

$$I_+\left[\Pi^{(j)} - c\right] = \begin{cases} 1, & \text{if } \left[\Pi^{(j)} - c\right] \geq 0, \\ 0, & \text{if } \left[\Pi^{(j)} - c\right] < 0. \end{cases} \tag{B2}$$

where $\Pi^{(j)}$ is a simulation-based estimate of the test statistic obtained given the new data $G_{(j)} = \left[G_1^{(j)}, \quad ... \quad, G_n^{(j)}\right]$, $j = 1, \ \ldots \ , K$ extracted from G as K *i.i.d.* draws.

Under the null hypothesis, Dufour (2006) established the following result for the MC confidence region $\hat{p}_K[G] \leq \alpha$, $0 < \alpha < 1$:

$$P[\hat{p}_K[G] \leq \alpha] = \alpha \tag{B3}$$

that holds under the integer values of $\alpha(K+1)$ with α denoting a chosen significance level.

C Mimicking Portfolio

This appendix describes a projection-based approach to assembling a mimicking portfolio for a non-tradable factor.

The idea of substituting a non-tradable factor with a return on its mimicking portfolio has been theoretically motivated in the literature (see Breeden, 1979; Huberman, Kandel and Stambaugh, 1987). It is common to obtain a return on such a portfolio as a weighted average of excess (less the risk-free rate) returns on base assets whose efficiency frontier coincides with that generated by the whole asset universe (see, for instance, Breeden, Gibbons and Litzenberger, 1989; Adrian, Etula and Tyler, 2014), that is

$$\tilde{F}_t^{mim} = \hat{w}' S_t, \quad t = 1, ..., T, \tag{C1}$$

$$\hat{w} = (\hat{w}_1, ..., \hat{w}_v)', \quad \hat{w}_i = \hat{b}_i \left(\sum_{i=1}^{v} \hat{b}_i\right)^{-1}, \quad i = 1, ..., v,$$

where $\tilde{F}_t^{mim}$ denotes a mimicking portfolio return for a non-tradable factor $\tilde{F}_t$, S_t is a $v \times 1$ vector of excess returns less the risk-free rate on v base assets and $\hat{\omega}$ is a $v \times 1$ vector with their associated weights. Also, $\hat{b}_i, i = 1, ...v$, are scalar OLS estimators for slope coefficients in a $v \times 1$ vector b obtained through the following projection:

$$\tilde{F}_t = a + b' S_t + z_t, \quad t = 1, ..., T.$$