UNIVERSITAT DE BARCELONA

Essays on Risk and Uncertainty in Economics and Finance

Jorge Mario Uribe Gil

PhD in Economics

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2017

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Thesis title:

Essays on Risk and Uncertainty in Economics and Finance

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Date:

December 2017

LIBERTAS PERFVNDET · OMNIA LVCE

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Acknowledgements

I would like to express my sincere gratitude to my supervisors, Helena Chuliá and Montserrat Guillen. They offered me their full support from the very beginning of my PhD. I have greatly benefited from our regular discussions, and their continuous and insightful feedback to my work. They did not only provide me a brilliant mentorship, which drew me along a path of academic growth and continuous learning, but also were supportive on a personal level. It has been a privileged working with them.

I also would like to thank Angelo Ranaldo and Paul Soderlind, in the Swiss Institute of Banking and Finance at HSG. My work greatly benefited from my discussions with them, while I was in St. Gallen as a visiting PhD Student. Angelo made of my stay in HSG a remarkably constructive experience, both on professional and personal levels.

My sincere gratitude goes also to Elisabet Viladecans–Marsal, and to Jordi Roca at the UB School of Economics. They always were very willing to help me every time that I resorted to them. Without them the journey of writing my thesis between Santiago de Cali (Colombia) and Barcelona (Spain), would have been unthinkable.

The warmest thanks go to Diana for her optimism and unconditional moral support, but also for her feedback to my own work. As an outsider of the profession (yet an extremely intelligent person) her views on my work have always helped me to notice relationships that I tend to overlook the first time that I approach a research question.

Financial support from COLCIENCIAS and Universidad del Valle in Colombia is gratefully acknowledged. The support from the Spanish Ministry of Economy, Industry and Competitiveness under grants ECO2015-66314-R and ECO2016-76203-C2-2-P, for the dissemination of my work in international congresses and academic journals is also acknowledged.

Chapter 1: Introduction

Uncertainty and risk have been fundamental concepts since the birth of modern science. Indeed various authors, including Bernstein (1998), claim that the interest in measuring and mastering the two phenomena is a threshold that separates modern times from the previous thousands of years of the history of humanity. In economics, Frank Knight was the first to postulate a distinction between uncertainty and risk, basically stating that the former could not be described by means of a probability measure while the latter could. According to both Knight (1921) and Keynes (1921, 1939), economic agents inhabit an environment of pervasive uncertainty and, therefore, there can be little hope of quantifying or forecasting economic variables, or even taking informed decisions that rely on quantitative measures of economic dynamics (in other words, for those authors, probabilities are incommensurable).

Today, the distinction between risk and uncertainty remains a lively topic for debate on the academic agenda. Indeed, several recent studies have attempted to explain decision- making under uncertainty, albeit oriented more towards the social conventions than towards the development of rational calculations. Accordingly, in this branch of the literature, there is a clear need to distinguish between the concepts, while measuring what can be measured and not losing sight of what cannot be quantified in probabilistic terms. Although of obvious importance in its own right, this extreme *Knightian* differentiation between risk and uncertainty leads to the impossibility of defining a probability space and prevents us from using any variation of the Ergodic Theorem in empirical studies. In turn, this leads to the impossibility of conducting any science at all (Hendry, 1980; Petersen, 1996).

Confronted by this panorama, the profession has moved from this Knightian extreme (fundamental) view of uncertainty and adopted a more promising approach to the concept. Today, it is widely accepted that uncertainty can (and indeed must) be measured, because it is intimately related to many economic phenomena. It is related for example to decisions on current and expected consumption, real and financial investment, business cycles dynamics, saving decisions, price formation, and to the possibility of consumption risk sharing (domestic and internationally). In short, it is at the core of the study of human wellbeing. Consistent with the discussion above, in the modern economic literature, uncertainty has generally been assimilated to a time-varying conditional second moment of the series under study, closely linked to underlying time- varying structural shocks such as terrorist attacks, political events, economic crises, bubble collapses, systemic risk materialization episodes, wars and credit crunches.

This thesis contributes to a better understanding of risk and uncertainty in the economics discipline. This overall objective implies the development of new tools to properly measuring, differentiating and managing risky and uncertain situations, the study of traditional investment strategies under uncertainty scenarios, and the quantification and analysis of the propagation of risk and uncertainty shocks to the international financial markets (stocks, banking and foreign exchange). Two main avenues are explored in this thesis to understand uncertainty, which reflect the current views in the profession regarding the topic. The first one consists on identifying uncertainty episodes based on a direct counting of economic and policy uncertainty-related keywords in the media. This approach has been pioneered by the work of Baker et al. (2016), which proposes an index of Economic Policy Uncertainty based on intensive text analysis and which can be used to gauge the level of macroeconomic uncertainty in a given period. The second view approaches the issue of measuring uncertainty from a residual perspective, which involves calculating the volatility of the series under study, only after their forecastable component has been removed (Jurado et al., 2015).

My research adds to the resolution of two problems in finance and economics: i) what is macro-financial uncertainty? : How to measure it? How is it different from risk? How important is it for the financial markets? And ii) what sort of asymmetries underlie financial risk and uncertainty propagation across the global financial markets? That is, how risk and uncertainty change according to factors such as market states or market participants. I have noticed that the same sort of questions arises in the study of different markets such as stocks, foreign exchange (FX) or banking. Thus, I provide a unified framework for the analysis of these issues in my dissertation. In the first part of this manuscript (chapters 2-4), I provide answers to the former questions, while in the second part I deal with the latter (chapters 5-6). My research has implications for asset pricing, risk management, financial stability, and the design of optimal monetary and macroprudential policy schemes.

Uncertainty, Trading, and Systemic risk

In Chapter 2, which is entitled "Momentum Uncertainties", I study the relationship between macroeconomic uncertainty and the abnormal returns of a momentum trading strategy in the stock market. I show that high levels of uncertainty in the economy impact negatively and significantly the returns of a portfolio of stocks that consist of buying past winners and selling past losers. High uncertainty reduces below zero the abnormal returns of momentum, extinguishes the Sharpe ratio of the momentum strategy, while increases the probability of momentum crashes both by increasing the skewness and the kurtosis of the momentum return distribution. Uncertainty acts as an economic regime that underlies abrupt changes over time of the returns generated by momentum strategies. In this way, I revisit a long-standing controversy in economics and finance, regarding the different nature of risk and uncertainty. I show that investment strategies such as momentum trading, which are precisely based on extrapolating immediate market past performance, seeking to predict future market trends, would likely fail when macroeconomic uncertainty is 'high'. On the contrary, when uncertainty is 'low', the usual assumption of treating uncertainty episodes as if they were risky situations works better, and extrapolation of current market trends may produce consistently significant abnormal returns. One pragmatic recommendation that derives from the main results of my research in this respect is not to trade momentum when uncertainty is above a certain threshold. Nevertheless, beyond this direct implication for trading, the study of momentum strategies, which are precisely based on extrapolating the immediate past in order to predict the immediate future, offers a unique opportunity to analyze the differences between risky and uncertain situations, both fundamental for economics and finance.

Also in the first part of my dissertation, in Chapter 3, "Measuring Uncertainty in the Stock Market", I seek to make three contributions to the study of uncertainty. First, I propose a new index for measuring stock market uncertainty on a daily basis (or what I refer to as financial uncertainty)[1]. The index considers the inherent differentiation between uncertainty and the common variations between the series (which I identify as risk). Recent contributions in the field have given rise to the methodological tools for performing the task using factor models (Jurado, Ludvigson and Ng, 2015).

[1] This index is updated regularly and is publicly available at http://www.ub.edu/rfa/uncertainty-index/

These proposals, however, have focused their attention on the use of macroeconomic variables to construct their indexes, as opposed to financial variables. Therefore, because of the low frequency of macroeconomic series, the proposals lack a desirable property of traditional proxies of uncertainty based on financial returns (such as VXO, VIX or credit-spreads): namely, practitioners and policy makers cannot trace their dynamics in real time. The second contribution of chapter 3 is to show how this financial uncertainty index can also serve as an indicator of macroeconomic uncertainty. I examine the circumstances under which my index might be thought to capture all the relevant information in the economy as a whole. I exploit the fact that information contained in hundreds, or even thousands, of economic indicators can be encapsulated by just a few prices of several stock market portfolios. Finally, I analyze the dynamic relationship between uncertainty and the series of consumption, interest rates, production and stock market prices, among others. This allows me to further our understanding of the role of (financial or macroeconomic) uncertainty, and to determine the dynamics of the economy as a whole.

Chapter 4: "Uncertainty, Systemic Shocks and the Global Banking Sector: Has the Crisis Modified their Relationship?" is the last chapter of the first part of my thesis. There, I explore the stability of systemic risk and uncertainty propagation among financial institutions in the global economy, and show that it has remained stable over the last decade. Additionally, I provide a new simple tool for measuring the resilience of financial institutions to these systemic shocks. My contribution to the literature in this essay is mainly the examination of the characteristics and stability of systemic risk and uncertainty, in relation to the dynamics of the banking sector stock returns. Thus, I provide evidence regarding the stability of the relationship between systemic shocks and the banks' responses over the last decade. This sort of evidence is new to the literature and is supportive of past claims, made in the field of macroeconomics (Stock and Watson, 2012), which hold that during the global financial crisis the financial system may have faced stronger versions of traditional shocks rather than a new type of shock. In this chapter, I also undertake an empirical study of the role of equity market uncertainty, as measured by Baker et al. (2016), as a systemic risk factor for the banking industry. Uncertainty is known to play a critical role in determining economic dynamics during episodes of crisis and, in recent years, its study has attracted much attention in the literature to account for the nonlinear negative dynamics that arise during episodes of economic distress (Bloom, 2009; Jurado et al., 2015). The inclusion of uncertainty as an observable factor enhances our understanding of the banking sector behavior during episodes of systemic stress in the financial markets. I report that for most of the banks analyzed, especially over the last decade, uncertainty is indeed a relevant consideration. As expected, more uncertainty leads to a reduction in equity prices in the banking industry, and this behavior has become more pronounced in the last few years, especially when compared to the situation 15 years ago. Finally, I emphasize the vulnerability of each institution to systemic shocks rather than the vulnerability of the system as a whole to the failure of one specific, perhaps important, financial institution. Thus, I identify systemically vulnerable financial institutions under scenarios of financial distress and provide a ranking of financial vulnerability that complements those already developed by the extant literature.

International propagation of risk

The second part of my dissertation explores the international propagation of financial risk, which is crucial to assess financial stability and capital market integration in the global capital markets. This second part consists of two chapters (5 and 6). In chapter 5, "Currency downside risk, liquidity, and financial stability", I aim to analyze downside risk propagation across global currency markets and the ways in which it is related to liquidity. The traditional study of return and volatility spillovers in currency markets imposes its own symmetry on the analysis, by implicitly assuming that for any given country the situation is roughly the equivalent of facing depreciation or appreciation pressures. This assumption is at the very least controversial. In the worst-case scenario, central banks may lean against the wind when appreciation pressures emerge on the horizon, to the degree that they are willing (or politically allowed) to do so. On the other hand, their response is much more restricted when faced by an episode of depreciation. Here, in the worst case they are bound by the (frighteningly) lower limit of the FX reserves. Thus, I make two primary contributions to the literature. First, I estimate tail-spillovers between currencies in the global FX market. I do so by closely adhering to what I consider a key element in the definition of a currency crisis proposed by Paul Krugman: "[it] is a sort of circular logic, in which investors flee a currency because they fear that it might be devalued, and in which much (though not necessarily all) of the pressure for such a devaluation comes precisely from that capital flight". Notice that by definition currency crises are related to periods of depreciation (or devaluation), and not to episodes of appreciation (or revaluation). Thus, in terms of financial stability, episodes of depreciation are more significant than those of appreciation. The tail-spillover estimates can be used to construct a new financial stability index for the FX market. This index is easy to build and does not require intraday data, which constitutes an important advantage. My second contribution is that I explore whether turnover is related to risk spillovers in global currency markets. World currencies can be expected to behave differently depending on how much investors trade them and, in turn, commonality may become evident by examining the dynamic spillovers in worldwide FX markets.

Chapter 6 is entitled "Spillovers from the United States to Latin American and G7 Stock Markets: A VAR-Quantile Analysis". This essay contributes to the studies of contagion, market integration and cross-border spillovers during both regular and crisis episodes by carrying out a multivariate quantile analysis. Most of the studies in this branch of the financial literature do not consider specific quantiles of the distributions and, therefore, they do not condition their results to specific market situations. Instead, they focus on the mean of the distributions, which could underestimate the real effects of an international shock. Even traditional quantile studies do not make any attempt to identify structural shocks by recourse to theory, nor are they able to analyze certain features of the shocks, such as their persistence, during different market scenarios. I focus the analysis carried out in this chapter on Latin American stock markets, which have been characterized by a highly positive dynamic in recent decades, in terms of market capitalization and liquidity ratios, after a far-reaching process of market liberalization and reforms to pension funds across the continent during the 80s and 90s. Moreover, the global financial crisis between 2007 and 2010 appears to have fostered financial flows into Latin American (LA) markets, as capital investors looked for diversification opportunities outside the mature markets, and as liquidity began to flourish around the globe, following persistently low market interest rates in the major economies. In general I documented smaller dependences between the LA markets and the US market than those between the US and the developed economies, especially in the highest and lowest quantiles. Nevertheless, I found an asymmetrical response to the shocks originating in the US market, depending on the conditioning quantile analyzed. This result holds regardless of whether the market under consideration is mature or emerging, an outcome that can be attributed to the phenomenon of flight-to-quality operating in the lowest quantiles, and a situation of liquidity spillovers between the markets in the highest quantiles. These results have obvious implications in terms of the optimal implementation of hedging strategies, portfolio diversification, and risk management, but also with regards to the optimal design of monetary and macroprudential policies.

The various chapters in this thesis can be found in:

[1]. Chuliá, H., J. Fernández, and J.M. Uribe, 2017, Currency downside risk, liquidity, and financial stability, working paper, University of Barcelona.

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

[3]. Chuliá, H., M. Guillen and J.M. Uribe, 2017, Spillovers from the US to Latin American and G7 stock markets: A VAR-quantile analysis, **Emerging Markets Review***,* 31:32-46.

[4]. Chuliá, H., M. Guillen and J.M. Uribe, 2017, Uncertainty, systemic shocks and the global banking sector: has the crisis modified their relationship?, **Journal of International Financial Markets, Institutions & Money**, 50: 52-68.

[5]. Uribe, J.M., 2017, Momentum Uncertainties, working paper, University of Barcelona.

I also contributed to the following original publications while writing my dissertation, which were substantially informed by the framework developed herein:

[1]. Chuliá, H., A.D. Pinchao, and J.M. Uribe, forthcoming, Risk Synchronization in International Stock Markets, **Global Economic Review**, accepted.

[2]. Chuliá, H., M. Guillen and J.M. Uribe, 2016, Modeling longevity risk with generalized dynamic factor models and vine copulae, **Astin Bulletin**, 46(1): 165-190.

[3]. Chuliá, H., M. Guillen and J.M. Uribe, forthcoming, Trends in the quantiles of the life table survivorship function, **European Journal of Population**, accepted.

[4]. Chuliá, H., R. Gupta, J.M. Uribe, and M. Wohar, 2017, Impact of US uncertainties on emerging and mature markets: Evidence from a quantile-vector autoregressive approach, **Journal of International Financial Markets, Institutions & Money**, 48: 178-191.

[5]. Mosquera, S., D. Manotas, D. and J.M. Uribe, 2017, Risk asymmetries in hydrothermal power generation markets, **Electric Power Systems Research**, 147: 154-164.

[6]. Mosquera, S., J.M. Uribe, and D. Manotas, 2017, Nonlinear empirical pricing in electricity markets using fundamental weather factors, **Energy**, 139(15): 594-605.

[7]. Holguín, J.S., and J.M. Uribe, 2017, The credit supply channel of monetary policy: Evidence from a FAVAR model with sign restrictions, revised and resubmitted to **Empirical Economics**.

Chapter 2: Momentum Uncertainties

Abstract

We show that high macroeconomic uncertainty significantly impacts the performance of stock momentum portfolios. Abnormal returns of winners-minus-losers strategies disappear when uncertainty is high, their Sharpe ratio collapses, skewness increases and kurtosis becomes more pronounced (increasing the probability of momentum crashes). There is also a significant reduction in the exposure to momentum by equity excess returns during high uncertainty states. The main findings here advise against trading momentum when uncertainty is high and emphasize the role of uncertainty as a *fundamental macroeconomic state* underlying the changes over time of momentum abnormal returns.

2.1. Introduction

We study the relationship between macroeconomic uncertainty and momentum abnormal returns and show that high levels of economic uncertainty significantly and negatively impact the returns of a portfolio of previous *winners* minus previous *losers* in the stock market. Uncertainty reduces the abnormal returns of momentum below zero, causes the Sharpe ratio of the momentum strategy to collapse, and raises the probability of momentum crashes by increasing the skewness and the kurtosis of the momentum return distribution. We also document a change in the momentum beta, which measures the exposure of excess equity returns to the momentum factor. Indeed, this exposure is significantly reduced for most of the portfolios analyzed during high uncertainty episodes. All these factors emphasize the importance of considering the level of economic uncertainty when deciding whether to trade momentum or not. Uncertainty acts as an *economic regime* that underlies abrupt changes in the abnormal returns generated by momentum strategies, which have been extensively documented in the literature (see, for example, Cooper et al., 2004, and Daniel and Moskowitz, 2016). The main pragmatic recommendation to be derived from our results is not to trade momentum when uncertainty is above a certain threshold.

Uncertainty in its original formulation (Knight, 1921; Keynes, 1921, 1939) implies that constructing a probability measure (for instance, seeking to build an accurate future forecast of a given event based on past realizations) is not feasible. As such, investment strategies such as momentum trading, which are based precisely on extrapolating the immediate past performance of winners and losers portfolios in order to predict future market trends, are likely to fail when macroeconomic uncertainty is 'high' enough. In contrast, when uncertainty is 'low', the usual assumption of treating uncertainty episodes as if they were risky situations works better, and the future extrapolation of market trends may produce consistently significant abnormal returns, as is the case with momentum portfolios.

We explore this hypothesis here by analyzing the monthly abnormal returns of a momentum portfolio (winners minus losers over the previous 2-12 months, WML hereinafter) from January 1927 to June 2017, almost a hundred years of data comprising NYSE, AMEX, and NASDAQ stocks[2]. We examine whether macroeconomic uncertainty (proxied by the Economic Policy Uncertainty index proposed by Baker et al., 2016) or economic activity (as measured by the dates of recession and expansion provided by the NBER over the last century) is the *economic state* that underlies abrupt changes in the abnormal returns of momentum strategies. In this respect, we adopt an approach that differs from that taken in the previous literature, which analyzes the dependence of momentum performance on a generic *market state*, presumably related to economic conditions (Gervais et al., 2001; Cooper et al., 2004; Daniel and Moskowitz, 2016; Ali et al., 2017). By so doing, it is our contention that we gain a better understanding of the nature of momentum trading and of the boundaries to its good performance, which are imposed by the economic uncertainty regime operating in the economy. We also discuss how, for the purposes of 'uncertainty management', to take advantage of recently developed proxies for measuring uncertainty in the macroeconomy, including the index developed by Baker et al. (2016).

This contribution is relevant because momentum continues to be a pervasive anomaly both in the cross-section (Asness et al., 2013) and over time (Moskowitz et al., 2012). Since Jegadeesh and Titman (1993) reported that previous winners in the stock market significantly outperform previous losers, thus making it possible to attain Sharpe ratios that exceed those of the market itself, momentum trading has remained a popular strategy among practitioners and of great interest to academics. However, this popularity seems to have weakened slightly due to the astonishing higher-order risks that momentum trading imposes on investors, including an extremely fat-tailed and negatively-skewed distribution of gains (Daniel and Moskowitz, 2016). The initial method of basically buying past winners and selling past losers has made room for more sophisticated strategies that use time-varying hedging mechanisms aimed

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[2] To construct the momentum portfolios, all stocks in the NYSE, Amex, and Nasdaq markets were ranked according to their returns from month $t-12$ to $t-2$. They were then classified into deciles according to NYSE thresholds. The WML strategy consists of shorting the lowest decile and taking a long position on the highest decile. The portfolios are value-weighted. The formation period for month t excludes the returns in the preceding month to avoid the short-term reversals documented by the literature. See Kenneth French's webpage for further details: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Benchmarks.

at reducing frightening momentum crashes (Blitz et al., 2011; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). Yet momentum trading continues to be practiced today.

If we turn our attention to asset pricing, it is not surprising that momentum remains something of a puzzle in explanations of excess returns. Countless factors have been proposed for analyzing this premium and its related anomalies (Campbell et al., 2016). However, the ever-growing set of factors explored to date does not yet provide a reliable substitute for momentum when it comes to explaining excess returns. One popular model –proposed recently by Fama and French (2015) includes, in addition to the three traditional factors of *market*, *size* and *book-to-market*, two factors related to *investment* strategies (conservative or aggressive) and a firm's *profitability* (robust or weak). Yet, in their new version of the classical three-factor model, Fama and French (2016) acknowledge the importance of including momentum within the set of regressors. In short, they claim that portfolios sorted according to winners and losers in the prior 2-12 months elude the explanation provided by the five-factor model, unless the momentum factor is included in the set of right-hand-side (RHS) variables.

On this playing field, it is quite natural that both rational (Johnson, 2002; Frazzini, 2006; Sagi and Seasholes, 2007; Liu et al., 2008) and behavioral explanations (Daniel et al., 1998; Hong and Stein, 1999; Cooper et al., 2004) have been offered to provide a definitive understanding of the momentum anomaly. The former seek to identify some kind of market friction, heterogeneous information, or firm-specific characteristics to account for momentum; while the latter resort to biases in the investors' perceptions to explain momentum profits. In these more behavioral models, the general reasoning embraces overconfident (Daniel et al., 1998; Chui et al., 2010) or over-reacting (Hong and Stein, 1999) investors who generate the momentum conundrum as new waves of information reach the market[3].

All in all, there is no completely satisfactory narrative as to what drives momentum. Doubts even exist as to whether momentum is really *momentum* or rather whether immediate past performance is actually a proxy for medium-horizon past performance (Novy-Marx, 2012). It seems that macroeconomic factors are unable to capture momentum profits after considering market microstructure concerns (Cooper et al., 2004), and that other sorts of explanation, such as the famous disposition effect, have been discarded as well (Birru, 2015). Clearly, momentum requires further exploration.

[3] See Barberis et al. (2015) and references therein for recent examples of extrapolative investors used to generate momentum. Hiller et al. (2014) also identify over-reacting and overconfident biases that are reinforced by media coverage.

If the elusive nature of momentum were not enough, its relationship with excess returns and systematic risk factors is also known to be non-linear. In other words, as momentum has time-varying market betas (Kothari and Shanken, 1992; Grundy and Martin, 2001), hedging using these betas does not work in real time. As Barroso and Santa-Clara (2015) document this occurs because the main source of predictability (and variability) of the risk implied by momentum strategies are not the betas, but the idiosyncratic conditional volatility. Put briefly, momentum does not appear to share with other more theoretically grounded factors the comfortable linearity ubiquitous in traditional equivalences with stochastic discount factor representations of market prices[4]. For this reason, its treatment means making room for time-varying risk prices, as functions of state variables[5].

This study contributes to the literature by identifying macroeconomic uncertainty as a major economic state underlying the performance of momentum strategies. Such an approach certainly provides more information and, hence, a better understanding of the nature and boundaries of the momentum strategy than when simply linking it to a *market state*. This study can be seen as a further step in the direction taken previously by Gervais et al. (2001), Grundy and Martin (2001), Cooper et al. (2004), Daniel and Moskowitz (2016) and Ali et al. (2017). Here, we estimate the abnormal returns, and other moments of the momentum return distribution, conditioning them on a state variable that measures macroeconomic uncertainty. In this way, we also add to a nascent strand in the financial literature that analyzes the impact of uncertainty on stock prices (Brogaard and Detzel, 2015; Segal et al., 2015; Bali and Zhou, 2016; Bali et al., 2017). Unlike these studies, we do not treat uncertainty as a *risk factor* in the set of RHS variables used to explain excess returns, but as a *market state* or *regime* that conditions both the abnormal returns of momentum above systematic risk factors, and the exposure of excess returns to it.

This study is possible thanks to recent advances in macroeconomics that have seen the construction of more appropriate measures of uncertainty, which can take into account its different nature with respect to risk or risk aversion. Some measures are a direct estimation of unexpected variations within a given system (Jurado et al., 2015; Chuliá et al., 2017), while others resort to a less probabilistic approach, based on a direct search for uncertainty-related keywords in the media (Baker et al., 2016). The latter approach is more compatible with the original *Knightian* or *fundamental* view of uncertainty

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

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

(Knight, 1921), since it does not rely directly on a probabilistic estimation for constructing the measure. For this and other reasons explained below, here we opt for the index developed by Baker et al. (2016) to conduct our analysis.

The modeling set up employed in all sections of this study considers two extreme states: one of *low* uncertainty and one of *high* uncertainty. We model endogenously the probability of transition between the two states in a smooth fashion. The same econometric machinery is used to estimate both the changing abnormal returns of momentum over time, and the changing exposure to momentum by excess returns, according to the uncertainty states. As highlighted above, and as expected, we document that momentum not only lacks relevance as a risk factor in regimes of high uncertainty for most of the portfolios analyzed, but it also becomes an extremely risky and unprofitable strategy. We advise against trading momentum when uncertainty is high (i.e. above a certain threshold of the lagged uncertainty index, namely the 90th percentile). Finally, it is worth noticing that our results hold after controlling for several proxies traditionally related to the time-varying returns of momentum, in particular, for the market state (for instance, a down market and the market volatility), and also after controlling for aggregate liquidity. Indeed, the inclusion of high uncertainty states in the explanation of momentum impacts the relationship between market liquidity and momentum returns, to the point of extinguishing it. This helps to explain the seemly contradictory finding recently reported by Avramov et al. (2016) regarding a positive and significant correlation between momentum profits and market liquidity.

2.2. Data

We analyze the returns of a portfolio of winners minus losers in the previous 2-12 months, taking the difference between the returns in the highest and lowest deciles of the portfolios, sorted according to prior performance (as in Barroso and Santa-Clara, 2015 and Daniel and Moskowitz, 2016). The portfolios, constructed each month, include NYSE, AMEX, and NASDAQ stocks. We condition the abnormal returns of momentum on a traditional Fama-French three-factor model, which allows us to explore a long time span covering almost a century of data (1,086 monthly observations). We also analyze the momentum betas of 25 value-weighted portfolios, sorted according to momentum and size, in the same period.

Most of the data used in this study were retrieved from Kenneth French's webpage[6]. The uncertainty index was taken from Baker et al. (2016) and is available online at http://www.policyuncertainty.com/. We used the historical Economic Policy Uncertainty (EPU) Index from January 1927 to February 2014 and chained it with the EPU index from March 2014 to June 2017. This

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

is the longest span available for the momentum portfolios in French's data-library. We also used the monthly returns of 25 Value-Weighted (VW) portfolios sorted according to size and momentum, likewise from French's library. We do not provide summary statistics of the factor-portfolios, the portfolios returns, or the uncertainty index, since they are well known in the literature and have been extensively documented elsewhere (see, for example, Fama and French, 2015 and 2016, Daniel and Moskowitz, 2016 and Baker et al., 2016). The stock level data used to estimate the turnover of the momentum strategy come from Wharton's CRSP database and consist of the universe of NYSE, AMEX, and NASDAQ stocks, with share codes 10 or 11, from December 1925 to December 2016. The stock level illiquidity index, employed in the estimations of section V, developed by Abdi and Ranaldo (forthcoming) is available online at: https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material. The monthly uncertainty index by Chuliá et al. (2017) used in section II is available online at: http://www.ub.edu/rfa/uncertainty-index/. Finally, the series of industrial production, employed in section II, comes from the FRED-database developed and maintained by the Federal Reserve of St. Louis: https://fred.stlouisfed.org/

2.3. Risk, Uncertainty and Economic States

Uncertainty and risk have been fundamental concepts in economics and finance since the birth of modern science. Indeed various authors, including Bernstein (1998), claim that the interest in measuring and mastering the two phenomena constitutes a threshold that separates modern times from the previous thousands of years of the history of humanity. In economics, Frank Knight was the first to postulate a distinction between uncertainty and risk, basically stating that the former could not be described by means of a probability measure while the latter could. Following Knight (1921) and Keynes (1921, 1939), economic agents inhabit an environment of prevalent uncertainty and, therefore, there can be little hope of quantifying or forecasting economic or financial variables. In other words, they considered the probabilities associated with the occurrence of economic events as incommensurable objects.

This approach to understanding uncertainty – known, today, as the *fundamental view of uncertainty* or *Knightian uncertainty* – while of obvious importance, makes it impossible to define a probability space and, therefore, to use any variation of the Ergodic Theorem to build the bases of empirical studies. It is for this reason that the profession has adopted a more flexible definition of uncertainty, particularly as regards macroeconomic uncertainty. Thus, uncertainty has come to be thought of as a time-varying conditional second moment, linked to underlying structural shocks, such as terrorist attacks, significant political events, economic crises, wars or credit crunches

(Bernanke, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1996; Leahy and Whited, 1996; Caballero and Pindyck, 1996; Bloom et al., 2007; Bloom, 2009; Bloom et al., 2013; etc.). Traditional proxies of uncertainty include stock returns or their implied/realized volatility (i.e., VIX or VXO), the cross-sectional dispersion of firms' profits (Bloom, 2009), estimated time-varying productivity (Bloom et al., 2013), the cross-sectional dispersion of survey-based forecasts (Dick et al., 2013; Bachmann et al., 2013), and credit spreads (Fendoğlu, 2014).

Although it indisputable that these uncertainty proxies have provided considerable insights, which, in turn, have allowed a better understanding of economic and financial decisions made under uncertainty, most of them have recently been criticized. The main criticisms concern the fact that these traditional proxies blend uncertainty with other notions (such as, risk and risk-aversion) and, in the case of analysts' forecasts, that they are only available for a limited number of series and so might reflect differences of opinion rather than uncertainty *per se* (Diether et al., 2002). In an effort to overcome these shortcomings, a new branch of the literature proposes measuring uncertainty either by directly counting economic and policy uncertainty-related keywords in the media (Baker et al., 2016) or by approaching the issue from a residual point of view, which involves calculating the volatility of the series under study, only after their forecastable component has been removed (Jurado et al., 2015; Chuliá et al., 2017).

Counting keywords is more compatible with the original *Knightian* view of uncertainty, as it does not rely directly on a probabilistic estimation for constructing the measure and, therefore, it may identify the fundamental difference between risk and uncertainty: under risk, a probability distribution based on past realizations seems natural and appropriate, under uncertainty, this situation does not hold. Moreover, the index proposed by Baker et al. (2016) is not specifically related to bad economic or market states, which are generally assimilated with economic recessions and market crashes, as we shall see. On the contrary, it may refer to both good and bad episodes of uncertainty. This point is crucial in what follows, because we know from the extant literature that recessions and bad market states negatively impact the performance of momentum strategies (Gervais et al., 2001; Cooper et al., 2004; Daniel and Moskowitz, 2016). Unlike the previous studies, here the interest lies in measuring the effects of generalized uncertainty, both good and bad, on momentum abnormal returns, on other moments of the conditional distribution of momentum portfolio returns, and on the exposure to momentum factors by excess equity returns.

Hence, the selection of the uncertainty proxy is essential in demonstrating that economic uncertainty, rather than economic activity (expansions and recessions), is the fundamental economic state underlying a significant deterioration in the performance of momentum strategies. As emphasized in the introduction, the intuition underpinning this reasoning is simple: momentum strategies resort directly to the extrapolation of past performance to predict the immediate future and such strategies are likely to fail under uncertain environments that are characterized precisely by the difficulty of defining a probability space based, for instance, on past realizations.

Table 2.1 shows the correlation between the EPU Index (Baker et al., 2016) – the main proxy for macroeconomic uncertainty used herein – and other variables frequently employed to account for uncertainty, including, the volatility of economic activity, market volatility and residual-based indexes of uncertainty. In examining these relations, we have focused on a set of measures that can be traced from the beginning of the estimation sample (January 1927) to the end (June 2017). In this way, we seek to preserve the internal coherence of the calculations reported across all the sections of this study.

Table 2.1

Correlation between Macro-Uncertainty and Macroeconomic/Market Variables

The table shows the correlation between the *EPU* index (Baker et al., 2016), used here as a proxy for macroeconomic uncertainty, and macroeconomic activity, macroeconomic volatility, total market volatility, 'good' and 'bad' volatility measures, and financial uncertainty. *IP* is the linearly de-trended index of industrial production for the US economy, *IP Vol* is the square of the monthly growth rate of IP, *Market RV* is the monthly realized volatility of the market portfolio using daily excess returns*, Bad RV* is the lower semivariance of the market portfolio using daily excess returns, *Bad RV* is the upper semivariance of the market portfolio using daily excess returns, and *F. Unc.* is a proxy for financial uncertainty constructed as in Chuliá et al. (2017), that is, using the residuals of an unobservable factor model of the excess equity returns. Semivariances were constructed following Barndorff-Nielsen et al. (2010). All the correlations reported are statistically significant at the 99.9% level of confidence. The sample period spans January 1927-June 2017 for a total of 1,086 observations. All the correlations are expressed in percentage points. Correlations between EPU and the other variables are highlighted in bold.

	EPU	*IP*	*IP Vol*	*Market RV*	*Bad RV*	*Good RV*	*F.Unc.*
EPU	-	**24.68**	**11.58**	**24.95**	**21.94**	**24.66**	**28.03**
IP	-	-	8.59	22.58	20.16	21.95	54.04
IP Vol	-	-	-	25.22	20.06	27.52	32.87
Market RV	-	-	-	-	94.18	91.25	51.32
Bad RV	-	-	-	-	-	72.18	44.52
Good RV	-	-	-	-	-	-	51.48
F. Unc.	-	-	-	-	-	-	-

As can be observed, the EPU Index is positively related to economic activity and its volatility; to market volatility (measured as the monthly realized variance of the market factor); to both good and bad market volatility measures (measured as positive and negative semivariances, as proposed by Barndorff-Nielsen et al., 2010); and, also, to other uncertainty indexes based on the estimation of a residual volatility, calculated after controlling for the forecastable component of the system volatility.

However, the main point to notice here is that none of these correlations exceeds 30%. That is, uncertainty, as it is proxied here, is not the same as economic activity, its volatility, or different market volatility measures. Interestingly, the index of financial uncertainty developed by Chuliá et al. (2017)[7], which generates nearly identical macroeconomic dynamics to that of the macro-uncertainty index proposed by Jurado et al. (2015) and available from July 1967 (see Chuliá et al., 2017), presents a stronger correlation with economic activity, as measured by industrial production and the other selected market volatility proxies, than that presented by the EPU Index (Baker et al., 2016).

Figure 2.1 shows the dynamics of the uncertainty index between January 1927 and June 2017, highlighting periods of high uncertainty (Panel A) and economic recessions (Panel B). High uncertainty episodes correspond in the plot to 20% of the sample associated with the highest uncertainty indicator values (217 observations), while economic recessions correspond to the months between a *peak* and a *trough* as dated by the NBER (211 observations). A visual inspection indicates that the two phenomena do not necessarily match. Indeed, in line with Harding and Pagan (2006), it is possible to calculate a synchronization statistic using two dummy variables: one indicating high uncertainty, the other indicating periods of recession. This statistic lies between 0 and 1, where 0 indicates that the two phenomena are perfectly discordant (i.e. when there is recession, there is never high uncertainty), and 1 indicates that they are perfectly concordant (i.e. when there is recession, there is always high uncertainty alike). A value close to 0.5 indicates that the two phenomena are largely independent. Here, the concordance statistic between recessions and high uncertainty is 0.48, indicating that the two phenomena are largely independent. This confirms our analysis (see correlations in Table 2.1) of the nature of uncertainty: while uncertainty may be present at the same time as an economic recession, it is not only present during such bad economic states. Thus, there are also many episodes of recession during which uncertainty is not particularly high.

As can be seen, the grey areas in Panel A match documented historical episodes, including economic recessions (1929, 1933, 1937, 1945), bubble

[7] Publicly available at http://www.ub.edu/rfa/uncertainty-index/

inflation and subsequent bursts and market crashes (1987, 2000-2002, 2007-2008), and episodes of financial and economic turmoil (2009-2011). We also see episodes of high uncertainty that are unrelated to 'bad' economic conditions. Consider for instance the high-tech revolution of the early-mid 1990s, which is identified as a state of high uncertainty. According to Segal et al. (2015, p. 117) "with the introduction of the world-wide-web, a common view was that this technology would provide many positive growth opportunities that would enhance the economy, yet it was unknown by how much". They refer to such situations as 'good' uncertainty.

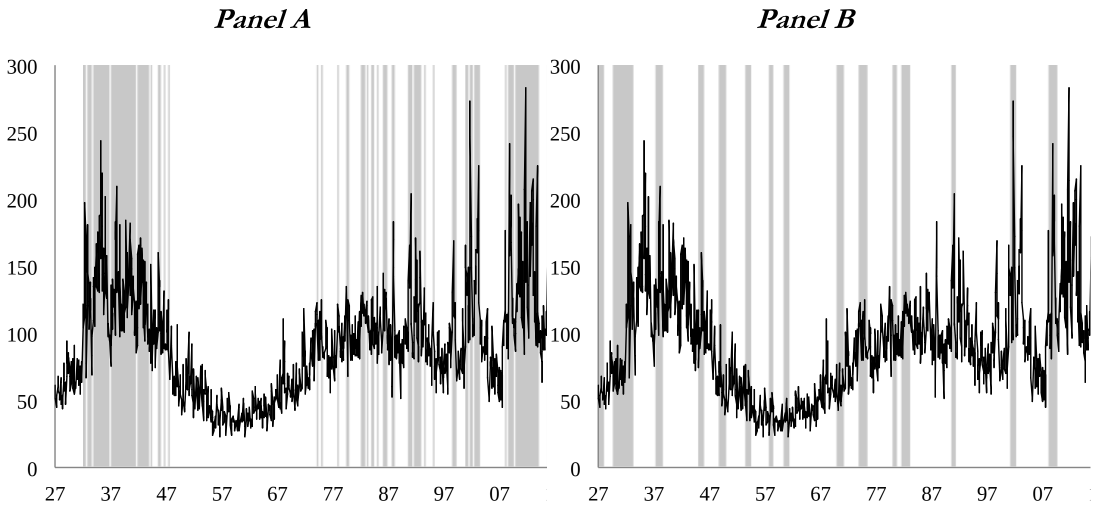

Figure 2.1 High uncertainty vs recessionary states. Panel A plots the index developed by Baker et al. (2016) and highlights the months with the highest levels of uncertainty (above the series 80th percentile). Panel B plots the same index and highlights recessions in the US economy as dated by the NBER. The sample period runs from January 1927 to June 2017. The concordance statistic between the highest uncertainty indicator (217 obs.) and the recession dummy variable (211 obs.) is 48.65%.

2.4. Abnormal Returns of Momentum Strategies

A. High Economic Uncertainty and Abnormal Returns.

One of the main contributions of this study derives from the estimation of equation 2.1:

$$WML_t = \pm\alpha \pm b_{RMRF}RMRF \pm b_{SMB}SMB_t \pm b_{HML}HML_t \ldots$$
$$\pm b_{H.UNC.}H.UNC_t \pm b_{REC}REC_t \pm other + noise_t, \quad (2.1)$$

which shows the regression of the monthly returns of a portfolio of WML on market (RMRF), small minus big (SMB) and high minus low (HML) factors. Depending on the specification, it also includes a dummy variable for high economic uncertainty (H.UNC); a dummy variable indicating macroeconomic contractions (REC), including the great depression and the great recession; other variables that account for 'good' and 'bad' economic uncertainty; and some interaction effects. The expected sign of the intercept in this regression is positive, which means that, after controlling for traditional risk factors, momentum is expected to offer statistically and economically significant abnormal returns. The expected signs of the loadings on the risk factors are negative, which implies that momentum is expected to diversify risk through the sample.

Following the working hypothesis forwarded in the introduction, the expected sign of the indicator variable of high uncertainty is also negative, because during episodes of high uncertainty investors may find it more difficult to construct accurate expectations about future winners and losers based on past performance – as momentum strategies seek to do – which in turn may reduce average abnormal returns of momentum. In line with the literature that identifies a negative relationship between economic states and momentum performance, the expected sign of the recession indicator is negative. Finally, we also analyze the effects of the interaction between periods of high economic uncertainty *and* recessions, which basically means 'bad news', as investors face both bad economic states and high uncertainty (H. BAD UNC); between high economic uncertainty and periods of economic expansion, which are naturally related to episodes of 'good' uncertainty (H. GOOD UNC); and, finally, the interaction between bad economic states and low economic uncertainty, which is mostly a situation of low bad uncertainty (L. BAD UNC).

The estimates corresponding to the different equation 2.1 specifications, and the associated t-statistics are presented in Table 2.2. These regressions were estimated using different thresholds to determine whether a situation might be considered to be of high uncertainty. Specifically, in Panels A, B and C, high uncertainty corresponds to the months in which the uncertainty index was above the 70th, 80th and 90th percentiles, respectively.

The first two columns of each panel show the estimated slopes and t-statistics, without including any additional variable on top of the traditional risk factors. As such, the values in these three columns are invariable across the three specifications. As expected, in the three panels, the abnormal returns of momentum (ALPHA) are positive, after controlling for the risk factors, and account for an abnormal return of 1.76% per month, which corresponds to 21.12% per year. This represents an impressive level of abnormal returns as emphasized by Barroso and Santa-Clara (2015), who report very similar results in this regard (1.75% per month, and 21% per year). Exposure to the risk factors is also negative, and statistically significant in these regressions.

Table 2.2
Momentum Abnormal Returns and Macroeconomic Uncertainty

The table shows the results of a regression of WML returns on market, size and value factors. It also shows estimates that include, on top of the three aforementioned factors, an indicator variable for high economic uncertainty regimes, H. UNC (that is, above the 70^{th}, 80^{th}, and 90^{th} percentiles in the EPU index); an indicator variable for recessionary periods (REC), an indicator variable of whether the economy is in a high uncertainty regime and an *expansion* period, referred to as high good uncertainty (H. GOOD UNC); and, an indicator of whether the economy is in a recession and a high uncertainty regime, referred to as high bad uncertainty (H. BAD UNC). Finally, the table also shows the estimated slopes of an indicator that identifies episodes of recession and low uncertainty regimes (below the respective thresholds), labeled as low bad uncertainty (L. BAD UNC). The impact of high uncertainty on the abnormal returns of momentum across different uncertainty thresholds is in bold.

	Panel A. 70th Percentile									
	b	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*
ALPHA	1.76	*8.43*	2.17	*8.78*	2.35	*8.83*	2.18	*8.84*	1.96	*8.44*
RMRF	-0.38	*-9.19*	-0.39	*-9.33*	-0.39	*-9.47*	-0.39	*-9.46*	-0.39	*-9.46*
SMB	-0.20	*-2.92*	-0.19	*-2.75*	-0.19	*-2.77*	-0.19	*-2.86*	-0.20	*-2.94*
HML	-0.74	*-12.14*	-0.73	*-12.14*	-0.73	*-12.15*	-0.73	*-12.14*	-0.73	*-12.15*
H.UNC			**-1.38**	*-3.78*	**-1.34**	*-3.00*				
REC					-0.93	*-1.79*				
H. GOOD UNC							-1.00	*-2.32*		
H. BAD UNC							-2.74	*-3.25*	-2.49	*-3.70*
L. BAD UNC									-0.23	*-0.38*
	Panel B. 80th Percentile									
ALPHA	1.76	*8.43*	2.16	*9.33*	2.34	*9.29*	2.17	*9.39*	1.97	*8.49*
RMRF	-0.38	*-9.19*	-0.39	*-9.36*	-0.39	*-9.52*	-0.39	*-9.56*	-0.40	*-9.55*
SMB	-0.20	*-2.92*	-0.19	*-2.89*	-0.20	*-2.98*	-0.20	*-2.93*	-0.20	*-2.97*
HML	-0.74	*-12.14*	-0.74	*-12.24*	-0.74	*-12.25*	-0.74	*-12.36*	-0.75	*-12.35*
H.UNC			**-2.00**	*-3.90*	**-1.97**	*-3.84*				
REC					-0.95	*-1.82*				
H. GOOD UNC							-1.37	*-2.42*		
H. BAD UNC							-4.22	*-4.29*	-4.31	*-4.24*
L. BAD UNC									-0.14	*-0.24*
	Panel C. 90th Percentile									
ALPHA	1.76	*8.43*	1.95	*8.90*	2.15	*8.87*	1.96	*8.98*	1.97	*8.57*
RMRF	-0.38	*-9.19*	-0.39	*-9.36*	-0.39	*-9.46*	-0.39	*-9.52*	-0.40	*-9.53*
SMB	-0.20	*-2.92*	-0.20	*-2.91*	-0.20	*-2.93*	-0.20	*-2.92*	-0.20	*-2.93*
HML	-0.74	*-12.14*	-0.74	*-12.28*	-0.74	*-12.30*	-0.76	*-12.53*	-0.76	*-12.49*
H.UNC			**-1.95**	*-2.78*	**-1.88**	*-2.75*				
REC					-0.99	*-1.89*				

H. GOOD UNC	-0.97	*-1.19*		
H. BAD UNC	-5.57	*-3.91*	-5.52	*-3.92*
L. BAD UNC			-0.45	*-0.82*

Interestingly, columns 3 and 4 of the table document that *abnormal returns of momentum disappear during episodes of high uncertainty*. For instance, when defining high uncertainty as the 20% (Panel B) of months with the highest values on the EPU index, the abnormal returns of momentum are 2.16% per month during low uncertainty regimes, and 0.16% during high uncertainty regimes (that is 2.16 minus 2.00%). The situation is similar if we focus on Panel A (from 2.17 to 0.79%, i.e. 2.17 - 2.00%) and on Panel C (from 1.95% to 0.00%, i.e. 1.95 - 1.95%). It seems that the more extreme the uncertainty, the greater the reduction in the abnormal returns of momentum (for example, when we go from the 70th to the 80th percentile), but this relationship is not linear. Rather it appears to be better described by an uncertainty threshold (because when we go from the 80th to the 90th percentile, the amount of abnormal returns does fall, but not as much as when we go from the 70th to the 80th percentile).

Columns 5 and 6 of Table 2.1 specifically test whether the reduction in the abnormal returns of momentum might be attributed to the underlying economic state (i.e. recessions), as opposed to the level of uncertainty. Here, we included a dummy variable indicating recessionary periods as dated by the NBER. The results are conclusive in all three cases. The effect of uncertainty on abnormal returns of momentum (that is, the coefficient of the uncertainty dummy variable) remains unaltered when we include the recession dummy variable. Moreover, while the high uncertainty indicator remains significant in all three panels, the recession variable presents the expected sign (negative), but does not present a t-statistic above 2.0 in any of the three specifications (although it is very close to doing so, especially, in Panel C). This provides solid evidence in support of the hypothesis that uncertainty is the main driver of the reduction in momentum profits, as opposed to bad economic states.

Columns 7 and 8 decompose the effect of uncertainty into 'bad' uncertainty situations, that is, when episodes of high uncertainty coincide with an economic recession, and 'good' uncertainty situations, in which uncertainty is high but there is an underlying economic expansion. Noticeably, a negative sign accompanies both sorts of uncertainty. That is, high uncertainty impacts negatively and significantly the performance of momentum portfolios, regardless of whether it is good or bad.

Columns 9 and 10 show an alternative decomposition, namely, estimates of recessions divided between those with high and those with low economic uncertainty. Here again the effect of recessionary states is always negative on

WML performance, regardless of the level of uncertainty. However, in the three threshold specifications considered, the negative effects of recessions with low economic uncertainty are not statistically different from zero. Moreover, the magnitude of the effect is also considerably smaller compared to that estimated in the case of an economic recession coinciding with high uncertainty, which is by far the most damaging state for momentum returns. During such periods, the average monthly abnormal returns of the momentum strategies fall, approximately, to within a range of between -2.00 and -2.34% (with an uncertainty threshold of 80% when considering columns 7 and 9, respectively).

B. Estimation of High Economic Uncertainty States

The estimates in Table 2.2 suffer the drawback of being subject to the exogenous, and perhaps arbitrary, selection of the threshold above which uncertainty is considered high. However, this does not affect the main result, i.e. that high economic uncertainty reduces (to the point of collapse) abnormal returns of momentum strategies, because the sign and the magnitude of the effect do not vary greatly with the threshold specification. Nevertheless, it is preferable to offer estimates that are not open to this criticism and which can provide a more accurate measure of the changes in the abnormal returns of momentum with the level of economic uncertainty.

For this reason, in Table 2.3 we show the estimates of a model in which the threshold signaling when economic uncertainty is above its ordinary levels has been estimated endogenously. To this end, we estimated a Smooth Transition Regression Model (STR) in line with McAleer and Medeiros (2008)[8] and Hillebrand et al. (2013)[9]. This framework is particularly suited to this purpose as it allows us to condition abnormal returns of momentum on the level of uncertainty in an endogenous fashion. The model assumes that the transition from states of low to high uncertainty is smooth and includes abrupt switches between the states as a special case.

Below, we describe a specialization of the general model that transits between two extreme regimes associated with *low* and *high* uncertainty in the economy. We estimated the following equation:

$$WML_t = G\left(\widetilde{\mathbf{X}}_t, u_t; \boldsymbol{\psi}\right) + \mathbf{W}_t' \boldsymbol{b}_w + \tilde{e}_t, \qquad (2.2)$$

[8] In this case, known as HARST, a multiple-regime smooth transition of the heterogeneous autoregressive model. We did not, however, consider autoregressive terms because no theoretical insights are to be gained from their inclusion in the model. Moreover, in contrast to our study, the authors of the original model use the model to estimate conditional volatilities of several returns of stock market indices in the global economy, using lagged variables to condition the transition.

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

where WML_t are the series of monthly returns of the winners minus losers strategy. $G(\widetilde{\mathbf{X}}_t, u_t; \boldsymbol{\psi})$ is a nonlinear function of the switching variables depending on $\widetilde{\mathbf{X}}_t$, which in this case consists of a constant (i.e. $\widetilde{\mathbf{X}}_t = \mathbf{1}$) employed to estimate the abnormal returns of momentum (α in equation 2.1), and u_t, which is the transition variable that governs the switching between the two regimes (namely the uncertainty index). It also depends on $\boldsymbol{\psi}$, which groups the parameters associated to G. $\mathbf{W}_t$ is a $T \times 3$ matrix containing the risk factors with linear (non-switching) loads and their associated coefficients $\boldsymbol{b_w}$, namely $\mathbf{W}_t = [RMRF_t, SMB_t, HML_t]$. Finally, $\tilde{e}_t$ is a vector of random noise residuals. This model can be further specialized as follows:

$$WML_t = \boldsymbol{b_0} + \boldsymbol{b_1} f(u_t; \gamma, c^*) + \mathbf{W}_t' \boldsymbol{b_w} + \tilde{e}_t, \tag{2.3}$$

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

$$f(u_t; \gamma, c^*) = \frac{1}{1+e^{-\gamma(u_t - c^*)}}, \tag{2.4}$$

where γ is the *slope* parameter and c^* can be understood as a *threshold* value that also needs to be estimated. This threshold separates low from high uncertainty regimes and is instrumental. Notice that $f(u_t;\, \gamma, c^*)$ is monotonically increasing in u_t and, therefore, $f(u_t;\, \gamma, c^*) \to 1$ as $u_t \to \infty$ and $f(u_t;\, \gamma, c^*) \to 0$ as $u_t \to -\infty$. For this reason $\boldsymbol{b_0}$ should be thought of as containing the abnormal returns of the momentum portfolio during a *low uncertainty* regime, while $\boldsymbol{b_0} + \boldsymbol{b_1}$ are the abnormal returns of the momentum strategy in a *high uncertainty* regime. Hence, the level of uncertainty determines the abnormal returns provided by the momentum portfolio.

Two interpretations of the STR model are possible. On the one hand, the model can be considered as a regime-switching model allowing for two regimes associated with the extreme values of the transition function $f(u_t;\, \gamma, c^*) = 0$ and $f(u_t;\, \gamma, c^*) = 1$, where the transition from one regime to another is smooth. On the other hand, the STR model can be considered as allowing a continuum of regimes, each associated with a different value of $f(u_t;\, \gamma, c^*)$. Here, we adopt the first interpretation.

In our calculations, $c^* = 121.55$ with a standard error of 12.75. This corresponds to the 80.15th percentile of the EPU index. Table 2.3 shows the estimates of the regression of WML returns on the risk factors and on the other covariates, as explained above. As can be seen, these estimates are largely similar to those for the 80th percentile in Table 2.2 (Panel B). But in this case they arise endogenously from the observed abnormal returns and the given model specification, since the uncertainty threshold was also estimated.

As expected, columns 7-10 indicate that a combination of high uncertainty regimes and recessions has the greatest impact on the performance of momentum strategies. Columns 7 and 9 show that abnormal returns fall to -2.18 (2.17 minus 4.35) per month, corresponding basically to a momentum crash. In contrast, and consistent with the analysis reported above, recessionary states unaccompanied by high uncertainty regimes do not present statistically significant effects on abnormal returns of momentum. This indicates that uncertainty appears to be the economic state that underlies momentum performance deterioration as opposed to contractions in economic activity.

Table 2.3
Abnormal Returns of Momentum and Macroeconomic Uncertainty with an Estimated Endogenous Threshold

The table shows the results of a regression of WML returns on market, size and value factors. It also presents estimates that include an indicator variable for high economic uncertainty regimes, H. UNC (above an endogenous threshold of the EPU index equal to 121.55); an indicator variable for recessionary periods (REC); an indicator variable of whether the economy is in a high uncertainty regime and an expansion period, referred to as high good uncertainty (H. GOOD UNC); and, an indicator of whether the economy is in a recession and a high uncertainty regime, referred to as high bad uncertainty (H. BAD UNC). Finally, the table also shows the estimated slopes of an indicator that identifies episodes of recession and low uncertainty regimes (below the endogenous threshold), labeled as low bad uncertainty (L. BAD UNC). The endogenous threshold was estimated using a Smooth Transition Regression model that consists of two extreme regimes, one of low uncertainty and one of high uncertainty. The transition variable in this model is the EPU index and the switching coefficient between the two regimes is the intercept, which measures the abnormal returns of momentum. The impact of high uncertainty on the abnormal returns of momentum is in bold.

	Endogenous Threshold (Percentile 80.15)									
	b	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*
ALPHA	1.76	*8.43*	2.16	*9.35*	2.35	*9.36*	2.17	*9.41*	1.97	*8.53*
RMRF	-0.38	*-9.19*	-0.39	*-9.38*	-0.39	*-9.53*	-0.40	*-9.70*	-0.40	*-9.61*
SMB	-0.20	*-2.92*	-0.19	*-2.88*	-0.19	*-2.89*	-0.19	*-2.90*	-0.20	*-2.93*
HML	-0.74	*-12.14*	-0.74	*-12.24*	-0.74	*-12.25*	-0.74	*-12.37*	-0.75	*-12.36*
H.UNC			**-2.20**	*-3.93*	**-1.99**	*-3.89*				
REC					-0.95	*-1.83*				
H. GOOD UNC							-1.37	*-2.42*		
H. BAD UNC							-4.35	*-4.29*	-4.15	*-4.81*
L. BAD UNC									-0.13	*-0.22*

C. Momentum Moments under High and Low Economic Uncertainty

To gain further insights into the evolving nature of momentum under different regimes of uncertainty, we estimated sample statistics of the momentum portfolio for the full sample and for two subsamples based on the above estimates of low and high uncertainty states (below and above the value of 121.55 on the EPU index). To construct comparable measures of skewness, variance, and kurtosis across the sub-samples, we decomposed the traditional formula for the *kth* central moment as follows.

Thus,

$$\bar{m}^k = \frac{1/N\sum_1^N (X_i - \bar{X})^k}{\left(\sqrt{1/N\sum_1^N (X_i - \bar{X})^2}\right)^k} = \frac{1/N\sum_1^N (X_i - \bar{X})^k}{\sigma^k}, \tag{2.5}$$

where $\bar{m}^k$, is the *kth* standardized central moment and N is the sample size. Then we have that:

$$\bar{m}^k = \frac{1/N(X_1 - \bar{X})^k}{\sigma^k} + \cdots + \frac{1/N(X_N - \bar{X})^k}{\sigma^k}. \tag{2.6}$$

If we group each term according to whether $X_i \leq c^*$ or $X_i > c^*$, that is, according to the set of low and high uncertainty regimes, respectively, we have:

$$\bar{m}^k = \frac{1/N\sum_1^{N_1} (X_i - \bar{X})^k}{\sigma^k} + \frac{1/N\sum_1^{N_2} (X_i - \bar{X})^k}{\sigma^k}, \tag{2.7}$$

where $N = N_1 + N_2$, and N_1, N_2 are the observations in the low and high uncertainty regimes, respectively. This can be written as:

$$\bar{m}^k = \frac{N_1/N\sum_1^{N_1} (X_i - \bar{X})^k/N_1}{\sigma^k} + \frac{N_2/N\sum_1^{N_2} (X_i - \bar{X})^k/N_2}{\sigma^k}, \tag{2.8}$$

if we define $\frac{\sum_1^{N_j} (X_i - \bar{X})^k/N_j}{\sigma^k} \equiv \bar{m}^k_{j=\{1,2\}}$, we can decompose the original equation as:

$$\bar{m}^k = \bar{m}_1^k \frac{N_1}{N} + \bar{m}_2^k \frac{N_2}{N}. \tag{2.9}$$

This is a weighted average of the sub-sample *kth* central moment, $\sum_1^{N_j} (X_i - \bar{X})^k/N_j$, standardized using the total-sample central moment σ^k, which in turn sums to the respective full-sample standardized moment, $\bar{m}^k$. The weights are the share of each uncertainty regime in the total sample.

These and other sample statistics, together with the traditional Sharpe ratio across and within subsamples, are reported in Table 2.4. Differences across the uncertainty regimes are notorious. While the Sharpe ratio for the WML strategy in the total sample is 0.52 (independent of the uncertainty level), it increases to 0.75 during the low uncertainty regime, and virtually collapses during episodes of high uncertainty (-0.09). Moreover, the average return of the momentum strategies when uncertainty is low stands at 14.14, but it becomes negative and falls to -3.07 when uncertainty is high. Skewness ranges from -2.01 in states of low uncertainty to -3.66 under high uncertainty. Likewise, standard deviation also increases by a factor of two, from 0.83 to 1.70. Finally, the (excess) kurtosis increases considerably from 16.60 to 20.77. If we consider the changes in the mean together with the other moments of the momentum distribution, we document a dramatic increase in the likelihood of momentum crashes during periods of high uncertainty (which, when using the selected threshold, naturally account for approximately 20% of the sample, $\frac{N_2}{N} = 19.98\%$).

Table 2.4
Momentum Moments under High and Low Uncertainty Regimes

	Total	*Low Uncertainty*	*High Uncertainty*
Maximum	26.16	26.16	24.99
Minimum	-77.02	-77.02	-45.16
Mean	14.14	18.39	-3.07
*Standard Deviation**	1.00	0.83	1.70
*Skewness**	-2.34	-2.01	-3.66
*Kurtosis**	17.42	16.60	20.77
Sharpe ratio	0.52	0.75	-0.09
Num. Obs.	N=1086	N_1 =871	N_2 =215

The rise in the Sharpe ratio following the abandonment of momentum trading when uncertainty is high is quite remarkable. For instance, if we compare the results in Table 2.4 with those reported by Barroso and Santa-Clara (2015), we see that while their volatility-managed strategy achieves an increase in the Sharpe ratio by an order of 1.83 (from 0.53 in the unmanaged version to 0.97 in the managed version), here there is an increase by an order of 1.44 (from 0.52 to 0.75) from a position of permanent momentum trading to one that excludes episodes of high uncertainty. Note that this result does not employ any time- varying scaling device, which would improve the Sharpe ratio even more, although this would imply higher transaction costs because of the portfolio rebalancing required each month, according to certain time-varying weights. Indeed, using stock level data from January 1927 to December 2016[10] we calculate the turnover of the WML strategy as 80.62% per month, and the turnover of a strategy consisting of abandoning the momentum position when uncertainty is high, as 74.20% monthly, which implies a reduction of the turnover of 6.42% in average, per month[11]. All in all, excluding high uncertainty episodes from our momentum position represents an

[10] Due to data restrictions in our subscription to CRSP, for the estimation of the turnover we had to exclude the last six months of our observations, namely, from January to June 2017.

[11] We calculate the turnover of momentum as in Barroso and Santa-Clara (2015), and as explained Appendix A.

economically significant improvement in terms of profitability, reduction of the transaction costs, and of the risk implied by the momentum strategy, which could be exploited by investors, in addition to other risk-management devices such as volatility scaling or other dynamic leveraging strategies.

The inspection of the kernel densities of the three cases (i.e. total sample, low and high uncertainties) complements the above analysis (see Figure 2.2). As can be seen, excluding high uncertainty episodes not only switches the returns distribution to the right, but also brings about a reduction in the losses tail. This is evident if we compare the solid black line, corresponding to high uncertainty states, with the red- and blue-dotted lines, corresponding to the total sample and the low uncertainty states, respectively.

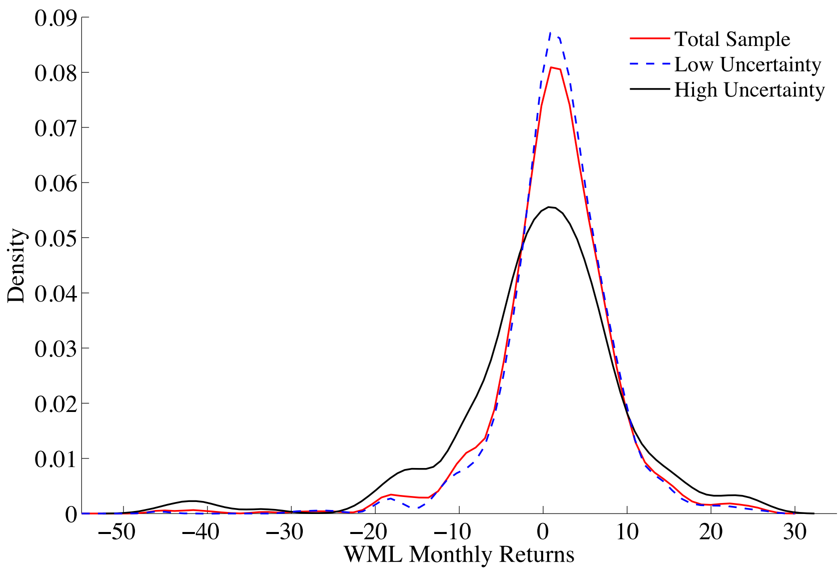

Figure 2.2. Densities of WML monthly returns under high and low uncertainty. The kernel densities were estimated with the observations for the total sample (black solid line), the low uncertainty regime (blue-dotted line) and the high uncertainty regime (red-dotted line).

D. Predictability of High Economic Uncertainty and Momentum Trading

A strategy like the one outlined above, which basically involves a curtailment of momentum trading when uncertainty is high, is feasible if we can predict with some accuracy the state of macroeconomic uncertainty in the following month. Thus, investors would be able to decide in real time whether to continue their allocation based on momentum (if uncertainty were low enough) or whether to curtail their momentum exposure (if uncertainty were high). In this section, we analyze this possibility by assessing the persistence and predictability of the EPU index developed by Baker et al. (2016) and by examining the variability of the high uncertainty threshold estimated around the 80th percentile. We also propose a strategy that can be implemented in real time.

In a preliminary analysis an augmented Dickey-Fuller test was conducted and the null of a unit root was rejected at the 99% level of confidence. In Table 2.5, we report the results of three regressions of the EPU index: on its first lag (first column); on two lagged months (third column); and, finally, on its third lag (sixth column). Besides the intercept of each regression (*Alpha*), and the autoregressive coefficient (*Rho*), the table also reports the out-of-sample R^2 (*OOR*^{2}) statistic proposed by Campbell and Thompson (2008). We drew on a sample of 240 months to run initial regressions and then used the estimated coefficients and the last available observation from the EPU index, to forecast one-step ahead (one, two or three months ahead for each model, respectively). Then, each month we used an expanding window of one observation to produce out-of-sample forecasts and compared these with the accuracy of the historical mean $\overline{EPU_t}$, as in equation 2.10:

$$R^2_{OOR2} = 1 - \frac{\sum_{t=T^*}^{T-1}(\hat{\alpha}_t + \hat{\rho}_t EPU_t - EPU_{t+1})^2}{\sum_{t=T^*}^{T-1}(\overline{EPU}_t - EPU_{t+1})^2}, \qquad (2.10)$$

where T^* is the initial training sample. $\hat{\alpha}_t$, $\hat{\rho}_t$ and $\overline{EPU_t}$ are estimated with information available only up to time *t*, to ensure that the forecast is feasible in real time.

As can be observed in Table 2.5, the EPU index is highly persistent. The one-lag autoregressive coefficient is around 0.81 (while the two-lag and three-lag coefficients are 0.72 and 0.67, respectively). Moreover, the OOR2 reaches 68% in the first case, and never falls below 47%, even when using three-month lagged information for the EPU index. This means that the level of future economic uncertainty can be predicted with relative accuracy, and that by looking only at the current level of economic uncertainty, decisions can be taken about the momentum exposure of a given portfolio allocation.

Table 2.5
Predictive Power of Lags on Current Uncertainty

The table shows the monthly estimates and t-statistics of a regression of current uncertainty on its own lags – that is, one month - L(1), two months - L(2) and three months - L(3). It also shows the in-sample R-squared – R^2, of the predictive regressions, and the out-of-sample R-squared, OOR^2, constructed as in Campbell and Thompson (2008). To estimate the OOR^2, we used a training sample of 240 months to run the initial models. Then the estimated coefficients and the last sample observation of the EPU index were used to forecast uncertainty in the following month. Then, each subsequent month was included in an expanding window of observations to produce out-of-sample forecasts and compared with the accuracy of the historical mean.

	L(1)	*t-stat*	*L*(2)	*t-stat*	*L*(3)	*t-stat*
Alpha	17.74	*9.82*	26.31	*12.29*	30.38	*13.37*
Pho	0.81	*45.13*	0.72	*33.70*	0.67	*29.80*
OOR^2	0.68		0.54		0.47	

Even if uncertainty is a persistent state, the estimation of the high uncertainty threshold may affect our decision as to whether to quit the momentum strategy in a given month – for example, if the uncertainty indicator is above a certain threshold. This threshold was estimated here at 121.55, which corresponds to the 80.15th percentile. If the uncertainty threshold (compared to the EPU index) is relatively stable over time, we can be confident about using it to inform our decision each month. In Figure 2.3 we show the time-varying 80.15th percentile of the EPU index from April 1972 (first half of the sample) to the end. We estimated the empirical percentile each month using the information up to this point, so as to ensure that this estimation was feasible in real time.

As can be observed, the uncertainty percentile is relatively stable. Indeed, the 80.15th percentile remained close to its sample mean (115.57) during the sample period, with a standard deviation of 2.03, which is 17.80 times lower than the standard deviation of the EPU index (36.17). This constancy allows us to rely on the estimated percentile when fixing a future threshold of high uncertainty.

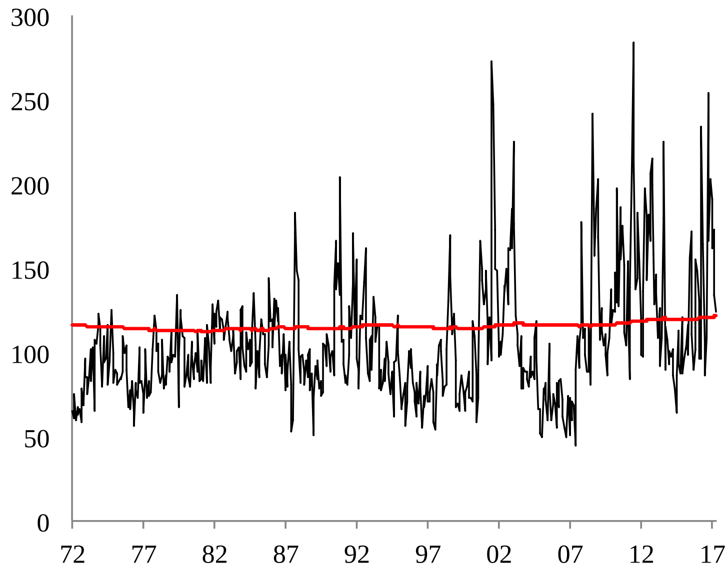

Figure 2.3. Time-varying high uncertainty percentile and EPU index. The figure shows the 80.15th percentile (red line) of the EPU index (black line) from April 1972 to the end of the sample.

E. Designing the Strategy

A simple portfolio strategy that consists on closing our exposure to momentum (both short and long positions) when we expect uncertainty to be high, leads to significant increments of the momentum profitability, and to an even more considerable reduction of the risks implied by the original momentum strategy. The threshold estimation at 121.55 presented before, was carried out using current uncertainty and, given that the one-lag autocorrelation coefficient of uncertainty is smaller than one (see table 2.5), we need a new (larger) threshold to implement our strategy in real time. We estimate this threshold at 145.02, using again our STR specification, but this time, employing lagged uncertainty as our state variable. Consistently, our proposed strategy consists of curtailing our exposure to momentum once we observed that last month uncertainty equals or is above 145.02. This number corresponds to the 90th percentile of the EPU index (see Table 2.2, panel C). In the second column of Table 2.6 we present the Sharpe ratio of this strategy alongside other moments of the return distribution of momentum, under low and high uncertainty states, while in Figure 2.4 we show the densities of the low and high expected uncertainty states, compared to the total sample density. Notice that this strategy leads to economic gains in terms of risk and return, even above those reported in Table 2.5 and Figure 2.3, and more importantly it is feasible in real time.

Table 2.6
Momentum Moments under High and Low Expected Uncertainty Regimes

	Total	*Low Uncertainty*	*High Uncertainty*
Maximum	26.16	26.16	24.99
Minimum	-77.02	-77.02	-60.17
Mean	14.12	17.90	-19.74
*Standard Deviation**	1.00	0.81	2.67
*Skewness**	-2.34	-1.49	-9.90
*Kurtosis**	7.81	7.05	12.77
Sharpe Ratio	0.52	0.73	-0.45
Num. Obs.	1085	976	109

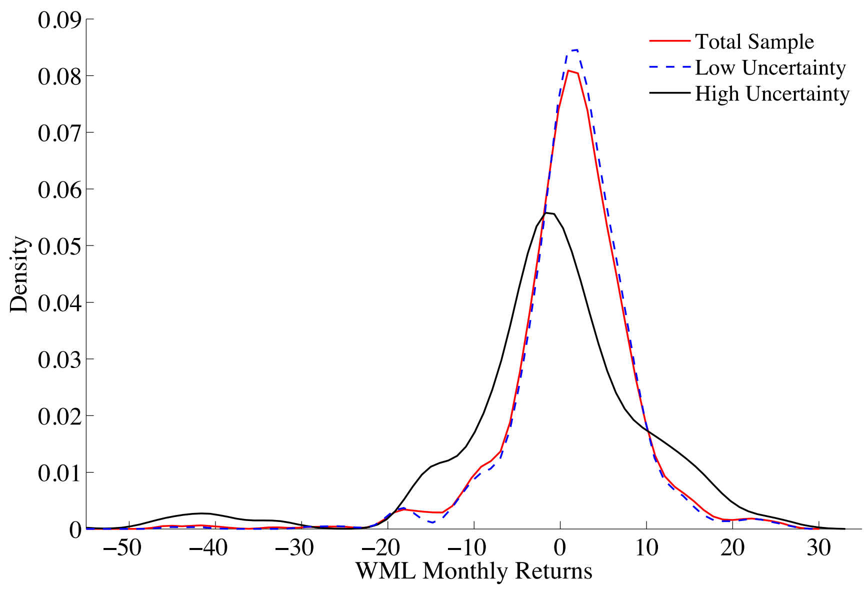

Figure 2.4. Densities of WML monthly returns under high and low expected uncertainty. The kernel densities were estimated with the observations for the total sample (black solid line), the low expected uncertainty regime (blue-dotted line) and the high-expected uncertainty regime (red-dotted line).

2.5. Excess Return Exposure to Momentum under Changing Economic Uncertainty

A. Uncertainty as an Economic State in the Pricing Equation

In this section, we show the results of the conditional three-factor model (Fama and French, 1993) augmented with a momentum factor (i.e. Cahart's (1997) model), following the same STR methodology as outlined above in equations 2.2-2.4. This allows us to condition the estimates of the momentum effects on the excess equity returns (momentum betas), and the intercept of the regression on the current economic uncertainty level. In so doing, we add to a nascent strand in the financial literature that analyzes the impact of uncertainty on stock prices (Brogaard and Detzel, 2015; Segal et al., 2015; Bali and Zhou, 2016). Unlike these authors, we describe a model that does not treat uncertainty as a *risk factor* common to all the analyzed portfolios in the RHS variables of the pricing equation, but as an economic regime, which has specific effects on each of the stock portfolios.

The reason for undertaking this exercise is the same as that outlined in section I. We expect uncertainty to impact investors' ability to construct an accurate probability distribution that can describe future winners and losers in the market and, as a result, during episodes of high uncertainty the momentum factor should lose relevance as an explanatory variable of excess returns. In other words, when uncertainty is high previous winners and losers do not provide a good forecasting ground of future winners and losers. Thus, momentum should not be priced in the cross-section of excess returns, or at least it should be priced to a lesser extent. In the same vein, a less relevant momentum factor should be associated with a lower adjustment of the four-factor model to the data and, therefore, with higher pricing errors, when uncertainty is high. Below, we present evidence to support these claims.

To this end, we estimated the following equation for each series of returns in 25 value-weighted portfolios sorted according to size and momentum:

$$EP_{it} = b_{0i}^{\alpha} + b_{0i}^{WML} WML_t + (\lambda_{1i}^{\alpha} + \lambda_{1i}^{WML} WML_t) f(u_t; \gamma_i, c_i^*) + \mathbf{W_t}' \boldsymbol{b_{wi}} + \tilde{u}_{it}, \quad (2.11)$$

where $EP = R - R_F$ are the excess returns, $\boldsymbol{b_{0i}} = [b_{0i}^{\alpha}, b_{0i}^{MOM}]$ should be thought of as containing the linear exposure of the excess returns to the momentum factor, and the intercept, during a *low uncertainty* regime, while $\boldsymbol{b_{0i}} + \boldsymbol{\lambda_{1i}}$, where $\boldsymbol{\lambda_{1i}} = [\lambda_{1i}^{\alpha} + \lambda_{1i}^{WML}]$, is the exposure to the momentum factor (and the intercept) in an extreme *high uncertainty* regime, $\mathbf{W_t} = [RMRF_t, SMB_t, HML_t]$ is a $T \times 3$ matrix containing the factors with linear (non-switching) exposure and their associated coefficients, such that $\boldsymbol{b_{wi}} = [b_{RMRF,i}, b_{SMB,i}, b_{HML,i}]$.

Table 2.7
Non-Linear Three-Factor Model Conditioned on the Level of Economic Uncertainty

The first five columns of the table show the estimates corresponding to the non-linear parameters in the smooth transition model. b_o^{α} and b_o^{MOM} are the estimates of the intercept and the momentum factor, respectively, in the low-uncertainty regime. λ_1^{α} and λ_1^{MOM} are the estimates of the changes in these parameters from low to high uncertainty states, respectively. The last five columns show the associated t-statistics for each parameter (against the null of non-significance). One model was estimated for each portfolio of 25 value-weighted portfolios sorted according to size and momentum. The variable that governs the transition between the two regimes was the economic policy uncertainty index. The estimation sample runs from January 1927 to June 2017, for a total of 1,086 observations.

Mom	Low	2	3	4	High	Low	2	3	4	High
			b_{0i}^{α}					t(b_{0i}^{α})		
Small	-0.15	0.03	0.40	0.20	0.44	-1.28	0.32	**3.69**	1.76	**2.53**
2	-0.14	-0.08	0.10	0.10	0.08	-1.61	-1.12	1.46	1.36	1.16
3	-0.66	0.09	0.12	0.08	0.09	**-2.78**	1.44	1.38	0.89	1.33
4	0.14	0.07	0.15	-0.02	0.08	1.30	0.80	1.59	-0.35	1.28
Big	-0.14	0.15	0.10	-0.03	0.10	-0.59	**2.13**	1.44	-0.42	0.65
			b_{0i}^{WML}					t(b_{0i}^{WML})		
Small	-0.34	-0.17	-0.15	0.00	0.05	**-20.69**	**-11.04**	**-8.98**	-0.25	1.87
2	-0.40	-0.13	-0.05	0.05	0.23	**-31.62**	**-11.42**	**-4.82**	**4.10**	**21.67**
3	-0.32	-0.18	-0.12	0.00	0.26	**-5.27**	**-20.01**	**-8.83**	-0.24	**28.01**
4	-0.51	-0.25	-0.12	0.08	0.28	**-30.89**	**-18.17**	**-7.41**	**9.17**	**30.48**
Big	-0.50	-0.25	-0.13	0.06	0.33	**-14.02**	**-25.01**	**-11.82**	**4.85**	**9.40**
			λ_{1i}^{α}					t(λ_{1i}^{α})		
Small	0.18	0.56	-0.01	0.35	-0.21	0.58	**2.67**	-0.03	1.03	-0.93
2	-0.21	0.45	-0.09	0.24	0.07	-1.17	**3.48**	-0.51	1.53	0.34
3	0.63	0.11	-0.07	-0.07	0.00	**2.53**	0.61	-0.61	-0.60	-0.01
4	-0.31	0.02	-0.04	0.40	-0.05	-1.55	0.18	-0.38	**2.44**	-0.25
Big	-0.10	0.13	-0.10	0.12	-0.25	-0.16	0.69	-0.99	1.21	-1.55
			λ_{1i}^{WML}					t(λ_{1i}^{WML})		
Small	-0.16	0.06	0.16	0.18	0.16	**-4.96**	**2.49**	**6.83**	**5.07**	**5.20**
2	0.07	-0.06	0.07	0.05	-0.07	**3.61**	**-4.06**	**3.68**	**2.67**	**-3.40**
3	-0.12	0.09	0.08	0.11	-0.07	-1.91	**4.58**	**5.06**	**6.06**	**-3.28**
4	0.10	0.09	0.08	-0.05	-0.05	**4.43**	**5.56**	**4.29**	**-3.40**	**-2.50**
Big	0.13	0.09	0.08	0.03	-0.06	**1.96**	**4.54**	**6.08**	**2.22**	-1.75

The non-linear estimates of the momentum factor exposures and the pricing errors (the intercepts) are presented in columns 1 to 5 of Table 2.7, together with their t-statistics in columns 6 to 10. In the first 5 rows, we report the estimates of the intercepts, corresponding to the low uncertainty regime, for each of the momentum (columns) and size (rows) portfolio quintiles. That is, the estimates of parameter b_o^{α} in equation 2.11. As is evident, only in four cases (out of 25) do these intercepts present a t-statistic above 2.0 and, therefore, for most of the models they are not statistically different from zero. In the second set of estimates, we report the estimates corresponding to the momentum exposures (rows 11 to 15, parameter b_o^{MOM}). In this case, the number of t-statistics above 2.0 rises to 22 (out of 25), which points to the significant role of momentum in explaining the excess returns during low-uncertainty regimes. All the coefficients associated with the momentum factor in the first 3 quintiles are negative, while they are close to zero in the fourth quintile, and positive for the quintile of the winners (the fifth). As expected, the most significant exposures, be they negative or positive, are found in the first and the fifth quintiles of the momentum distribution.

In rows 11 to 15 and 16 to 20, we can observe the estimates of $\boldsymbol{\lambda_{1i}} = [\lambda_{1i}^{\alpha} + \lambda_{1i}^{WML}]$, that is, the estimates of the changes in the non-linear parameters from a low to a high uncertainty regime. Once again, the changes in the intercept are statistically insignificant most of the time (except in four cases). The point estimates of these changes are as likely to be negative (12) as they are positive (13), regardless of the corresponding quintile. In marked contrast, most of the changes in the momentum factor are associated with a t-statistic above 2.0 (here, there are only two exceptions in which the t-statistic equals 1.75 and 1.97). In most cases, the changes are positive for the portfolios in quintiles 1 to 4 (with four exceptions) and negative for the portfolios in the fifth quintile (with one exception). These results seem to identify the momentum factor as the determinant of the non-linearity documented above, as opposed to the equations' intercepts (pricing errors).

In Panel A of Figure 2.5 the magnitude of exposure to momentum is shown under low and high uncertainty regimes. That is, for each portfolio, we plotted the coefficient b_o^{MOM} (in black) that measures the effect of momentum on excess returns, when uncertainty is low, and alongside it (in red) the exposure to momentum under a regime of high uncertainty (that is, $b_o^{MOM} + \lambda_1^{MOM}$). In Panel B, the model's estimated intercepts in both low uncertainty regimes (blue bars on the left) and high uncertainty regimes (grey bars on the right) are shown. The figure also displays 1.96 standard errors calculated as in the first regime. As expected, the portfolios most exposed to momentum are those in the first and the fifth quintiles of the momentum sort: the former in a negative sense, the latter positively. Between the two extreme quintiles, momentum exposure increases from losers to winners monotonically. Fama and French

(2016) document the same pattern, which is to be expected given the way in which the WML portfolios are constructed.

Panel A. Momentum Exposures *Panel B. Intercepts (Absolute Value)*

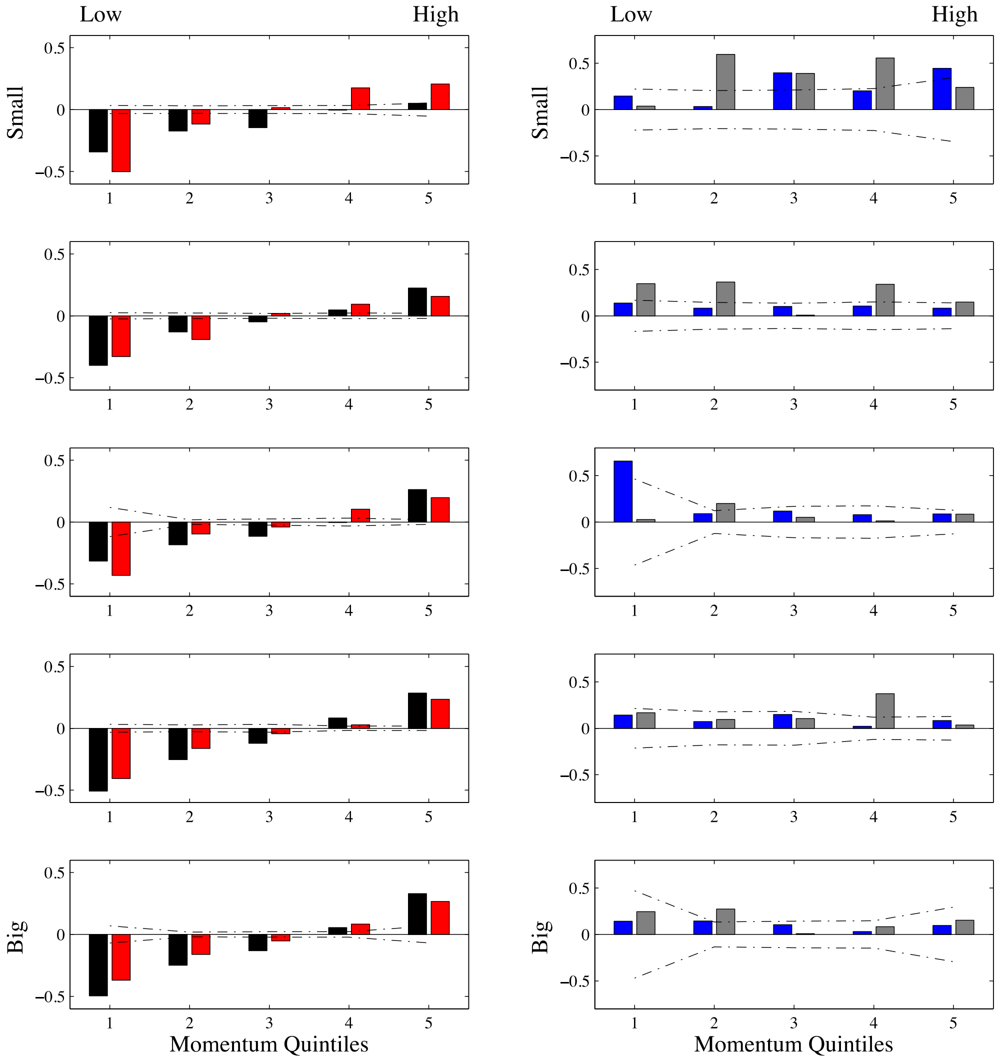

Figure 2.5. Changes in the effect of momentum on excess returns and pricing errors. Panel A shows the coefficients associated with momentum in the "low uncertainty" (black bars on the left) and "high uncertainty" (red bars on the right) regimes. Panel B shows the absolute value of the model's intercepts in the "low uncertainty" (grey bars on the left) and "high uncertainty" (blue bars on the right) regimes. The dotted line corresponds to 1.96 times the standard error of the coefficient in the linear part of the model. These estimates were obtained using 25 value-weighted portfolios sorted according to size and momentum. The estimation sample runs from January 1927 to June 2017, for a total of 1,086 observations.

Nevertheless, by visual inspection of the figure, we can confirm our main conclusion from Table 2.7: that is, exposure to momentum by the excess equity returns changes considerably depending on the regime of economic uncertainty. Indeed, if we divide the momentum portfolios into three groups: a) those that show an increase in their exposure to momentum when uncertainty is high, preserving the same sign in both low and high uncertainty states; b) those that undergo a change in the sign of their exposure during high uncertainty states, compared to that presented in low uncertainty; and c) those that show a decrease in their exposure to momentum as they move from episodes of low to high uncertainty, preserving the same sign in both cases, then we find that a generalized reduction in exposure to momentum (that is group c) is the most likely case (15 out of 25). The remaining portfolios either present a change in the sign of their exposure to momentum (four cases), or strengthen their low uncertainty exposure to it (six cases).

To sum up, momentum betas become extremely volatile in regimes of high uncertainty, with just 24% of portfolios displaying a stronger exposure to the momentum factor, in the same direction as that shown during regimes of low uncertainty. These cases are mainly located in small firms (first and second quantiles in the size sorting account for four out of the six cases). All in all, *during regimes of high economic uncertainty, momentum relevance as a risk factor disappears in relation to most portfolios, while it only keeps relevance for a few small firm portfolios*.

These results can be attributed to the fact that during episodes of high uncertainty, exposure of excess returns to the momentum factor falls, because investors lack the information required to construct an accurate probability of the expected future distribution of winners and losers, having to rely on the last information available before the current period, and moreover they are aware of this. This situation occurs precisely because uncertainty is related to the changing economic environment, in which it is more difficult to forecast than it is in a regular market. In short, investors are aware of possible changes in the market fundamentals that might affect the future performance of firms and portfolios.

These results are also consistent with the hypothesis that the cognitive or behavioral biases, which are generally used to explain momentum (see, for example, Daniel et al., 1998, and Hong and Stein, 1999), tend to operate under low uncertainty regimes. Under such circumstances, they reinforce market trends, which means momentum profits depend on the market state (Gervais et al., 2001; Cooper et al., 2004), but they tend not to operate, at least with the same magnitude, under high uncertainty regimes. During episodes of high uncertainty, either the number of 'momentum traders' falls or the 'reinforcing' and 'self-attribution' biases disappear, depending on the narrative.

This mechanism suggests a differentiated way in which investors form their expectations, according to the level of generalized uncertainty in the economy.

While under more regular *risky* circumstances, when uncertainty is low, they are more prone to the traditional biases documented by the literature (and which may explain the momentum anomaly), under more extreme *uncertainty* (which they do not assimilate as risk), the investors resort to a more cognitive approach to investment, and therefore the momentum conundrum disappears.

B. Pricing Errors of the Three-Factor Model under High and Low Uncertainty.

The discussion above is confirmed by decomposing the pricing errors of the Fama-French three-factor model augmented with the WML factor during episodes of low and high uncertainty. Table 2.8 exhibits $A|a_i|$, which is the average of the absolute values of the intercepts in each regime and in the linear specification. The second set of estimates in the table shows $A|a_i|/A|\tilde{r}_i|$, which was calculated as the average of the absolute values of the intercepts in each regime divided by the average of the absolute values of $\tilde{r}_i$. $\tilde{r}_i$ is the dispersion of the equity premium *temporal means* around their *cross-sectional mean*. That is, we calculated the temporal means for each equity premium series as $\bar{r}_i = \sum_T ep_{it}/T$. Here, T varies according to the number of observations in each regime and in the total sample. Then, we subtracted from each $\bar{r}_i$ the cross-sectional mean: $\bar{\bar{r}} = \sum_N \bar{r}_i/N$, such that $\tilde{r}_i = \bar{r}_i - \bar{\bar{r}}$. Finally, Table 2.7 also reports $A(a_i^2)/A(\tilde{r}_i^2)$, this is the average squared intercept over the average squared value of $\tilde{r}_i$ corrected for the sampling error in the numerator and denominator. We calculated $A|a_i|$ in the low uncertainty regime, as the average absolute value of the intercepts in this regression, and $A|a_i|$ in the high uncertainty regime, as the average absolute value of the same intercepts plus d_i in the following equation:

$$R_{it} - RF_t = a_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + m_i WML_t \ldots$$
$$+ d_i d_{it}^{unc} + i_i d_{it}^{unc} * WML_t + e_{it}, \quad (2.12)$$

where d_{it}^{unc} indicates whether the probability of the high uncertainty regime is higher than 0.5. We also constructed separate series of $\tilde{r}_i$ for high and low uncertainty regimes, according to the probability $f(u_t; \gamma, c)$. When $f(u_t; \gamma, c) > 0.5$, we classified the observation in a month belonging to a high uncertainty regime. In contrast, when $f(u_t; \gamma, c) \leq 0.5$, we classified the observation in a month belonging to a low uncertainty regime.

Comparing the linear model with the non-linear estimates, we found that the linear model always houses smaller pricing errors on average than the low or high uncertainty regimes separately. Although this might at first glance appear surprising, as one would naively expect this intercept to lie in-between the intercepts of the two uncertainty states, this is not in fact the case. It is perfectly feasible for the linear model to exhibit an average intercept below that of both the low and the high uncertainty regime. This does not point to some superior qualities of the linear model, but rather that the value of the intercepts in the linear specification, on average, conceals temporal pricing errors that are actually larger, but with different signs, in each of the two uncertainty states. On occasions the linear model overprices and on others it underprices the LHS portfolios and, as a result, part of the errors is cancelled out when the full-sample intercept is estimated (because of time-averaging, as opposed to cross-sectional averaging, which is taken into account using the absolute value operator as was explained above).

In short, Table 2.7 shows that the pricing errors are consistently higher during episodes of high uncertainty, even after controlling for the excess return variance in each regime. The reduction in exposure to the momentum factor caused by the change in the level of economic uncertainty leads to a reduction in the model adjustment, which is consistent with our previous discussion.

Table 2.8
Pricing Errors in High and Low Uncertainty Regimes

The table shows the statistic $\frac{A|a_i|}{A|\tilde{r}_i|}$. $A|a_i|$ is the average of the absolute values of the intercepts in each regime. $A|\tilde{r}_i|$ is the average of the absolute values of $\tilde{r}_i$. $\tilde{r}_i$ is the dispersion of the equity premium *means over time* around their *cross-sectional mean.* $A(a_i^2)/A(\tilde{r}_i^2)$ is the average squared intercept over the average squared value of $\tilde{r}_i$. We estimated a nesting model as:

$$R_{it} - RF_t = a_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + m_i WML_t + d_i d_{it}^{unc} + i_i d_{it}^{unc} * WML_t + e_{it},$$

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

5X5 size-momentum portfolios	$A\|a_i\|$	$A\|a_i\|/A\|\tilde{r}_i\|$	$A(a_i^2)/A(\tilde{r}_i^2)$
Linear Model	0.11	0.36	0.12
Low Uncertainty	0.15	0.40	0.21
High Uncertainty	0.20	0.60	0.40

2.6. Uncertainty, Liquidity and Market States

In this section we examine whether our findings regarding the significant impact of high uncertainty states on momentum abnormal returns hold, after controlling for several proxies for the market state (different from economic activity, as measured by the NBER recession series) and, in particular, for market liquidity. Recently, Avramov et al. (2016) documented that momentum profits are markedly larger in liquid market states. Their finding is not explained by variation in liquidity risk, exposure to traditional risk factors, or changes in macroeconomic condition, etc. As explained by these authors, this fact contradicts a basic intuition in finance, namely, that arbitrage is easier when markets are most liquid, and therefore momentum profits should be lower in more liquid markets. We show in Table 2.9 that this is not longer the case, once you account for high uncertainty states (both, above the 80^{th} percentile of current uncertainty- actual uncertainty-, or above the 90^{th} percentile of lagged uncertainty- expected uncertainty). Hence, the reason for the counter intuitive finding is that market liquidity is positively correlated with economic uncertainty, in particular with high uncertainty episodes.

We used as a proxy for aggregate market liquidity the average of the stock liquidity measure recently proposed by Abdi and Ranaldo (forthcoming). This measure has several advantages over the competing alternatives. For example, compared to other low-frequency estimates, this method utilizes wider information (i.e. close, high, and low prices); it also provides the highest cross-sectional and average time-series correlations with the TAQ effective spread; and it delivers the most accurate estimates for less liquid stocks. Nevertheless, the results reported in Table 2.9 remain unaltered if we employ instead other measures of market liquidity such as the ones developed by Pastor and Stambaugh (2003) or Corwin and Schultz (2012). We also consider the effects of market volatility and bad market states, which are known to have a significant effect on the time-varying momentum profits (see for instance, Cooper et al., 2004; Wang and Xu, 2015; and Daniel and Moskowitz, 2016). As can be observed in Table 2.n one of these factors reduces the economically and statistically significant impact of high uncertainty on momentum abnormal returns (see columns 11-14). Moreover, although such factors are statistically significant when they are included *individually* in the RHS of the explanatory regressions of the WML returns (columns 3-8), only high uncertainty remains significant when all the factors are included *simultaneously* (columns 13-14).

In this table, unlike most of the tables in this manuscript, the reported t-statistics were constructed using Newey-West's robust standard errors, but the conclusions above remain unaltered if instead we had reported regular standard errors (as is frequently done in the literature). As so, this constitutes and additional robustness exercise.

Table 2.9
Actual and Expected Uncertainty, Market States and Liquidity

The table shows the results of a regression of WML returns on market, size and value factors. It also presents estimates that include an indicator variable for high economic uncertainty regimes, H. UNC (above an endogenous threshold of the EPU index equal to 121.55, roughly equivalent to the 80th percentile); for high economic expected uncertainty one month ahead, EXP. H. UNC. (above 145.02, equivalent to the 90th percentile); an indicator variable for bad market states, DOWN (which is a dummy variable that takes the value of 1 if the return on the value-weighted market index during the past 24 months ($t-24$ to $t-1$) is negative, and 0 otherwise, following in Cooper et al. (2004) and Avramov et al. (2016)); an indicator variable of market illiquidity, ILIQUID, proxied by the average of stock level illiquidity developed by Abdi and Ranaldo (forthcoming); and Market RV, which is the monthly realized volatility of the market portfolio using daily excess returns. The sample for the reported regressions runs from January 1929 to December 2016. The endogenous thresholds were estimated using a Smooth Transition Regression model that consists of two extreme regimes, one of low uncertainty and one of high uncertainty. The transition variable in each model were the EPU index and the EPU index lagged one month, for current and expected uncertainty, respectively. The switching coefficient between the two regimes is the intercept, which measures the abnormal returns of momentum. The impact of high uncertainty on the abnormal returns of momentum is in bold. In this table Newey–West (1987) adjusted standard errors were used to construct the reported t –statistics, *t(b)**.

	Robustness checks													
	b	*t(b)**	*b*	*t(b)**	*b*	*t(b)**	*b*	*t(b)**	*b*	*t(b)**	*b*	*t(b)**	*b*	*t(b)**
ALPHA	1.7	9.0	2.0	9.2	3.3	4.6	2.0	9.0	2.9	4.7	2.8	4.5	2.8	4.7
RMRF	-0.4	-4.4	-0.4	-4.3	-0.4	-4.3	-0.4	-4.4	-0.4	-4.3	-0.4	-4.4	-0.4	-4.3
SMB	-0.2	-1.3	-0.2	-1.2	-0.2	-1.2	-0.2	-1.3	-0.2	-1.2	-0.2	-1.2	-0.2	-1.2
HML	-0.7	-4.3	-0.7	-4.4	-0.7	-4.3	-0.7	-4.3	-0.7	-4.4	-0.7	-4.4	-0.7	-4.5
DOWN		0.0	-1.2	-1.9					-0.8	-1.4	-0.7	-1.2	-0.7	-1.3
ILIQUID t-1					-1.0	-2.1			-0.6	-1.3	-0.3	-0.8	-0.4	-1.0
MVOL t-1							-1.3	-1.9	-0.8	-1.3	-0.7	-1.3	-0.6	-1.2
HIGH UNCERTAINTY											-1.5	-2.5		
EXP. HIGH UNCERT.													-2.1	-2.5

We carried out additional robustness exercises, which are reported in the Appendix. For example, in Appendix B we show that uncertainty does not have a smoothed impact on momentum returns. That is, that the impact of uncertainty (as a continuous variable) on WML abnormal returns changes radically after uncertainty has overpassed the high uncertainty threshold estimated herein. Indeed, this relation is *positive and insignificant* when uncertainty is low, while it is *negative and significant* when uncertainty is high. This supports our methodological choice of threating uncertainty as a state, and therefore as a binary variable, instead of approaching it as a continuous-risk factor. In Appendix C, we show that the results discussed above hold, not only for the WML portfolio, but also for its two legs. In other words, the impacts of uncertainty are largely the same on both winners and losers in the momentum portfolio. Finally, in Appendix D we report the estimates corresponding to a shorter sample from June 1992 to June 2017, (the last 300 observations in our sample). Remarkably, even tough momentum abnormal returns decrease in the more recent sample, as has been documented elsewhere, our results regarding the relationship between uncertainty and momentum profits reamin unaltered.

2.7. Conclusion

We document a non-linear behavior of momentum abnormal returns and other moments of the momentum return distribution, conditioning on the level of economic policy uncertainty, which we employed herein as a proxy for generalized macroeconomic uncertainty. Our results emphasize the role played by uncertainty to explain the abrupt changes in momentum profitability, which have been extensively documented in the literature. By examining the role of uncertainty in momentum strategies, we are able to provide a better understanding of the nature of momentum and of the natural boundaries imposed by the level of economic uncertainty on momentum trading and profits.

These findings have obvious implications for asset pricing and portfolio allocation. Specifically, we have explored *momentum moments* under two regimes of uncertainty. Thus, we have found that the abnormal returns produced by momentum disappear during regimes of high uncertainty, their Sharpe ratio collapses, the kurtosis of the momentum strategy increases and their skewness becomes more pronounced, increasing the likelihood of momentum crashes.

A simple recommendation that can be derived from these main results is not to trade momentum when uncertainty is expected to be high. This decision can be based on forecasts of economic uncertainty (which tends to be a highly persistent process), and the use of the threshold separating the expected uncertainty regimes (estimated here at the 90th percentile of the EPU index), to determine whether to curtail our momentum exposure. This strategy has the additional advantage of reducing transaction costs, via the direct reduction in the turnover of the momentum portfolios.

Nevertheless, beyond this direct implication for trading, the study of momentum strategies, which are precisely based on extrapolating the immediate past in order to predict the immediate future, offers a unique opportunity to analyze the fundamental differences between risky and uncertain situations. Both of which are fundamental for economics and finance.

Our results and conclusions hold after controlling for traditional proxies for the market state, such as economic activity, down markets and market volatility. They are relevant for the two legs of the momentum portfolio (winners and losers), and describe equally well a long time series sample spanning January 1927-June 2017, and more recent ones. High uncertainty regimes are able to explain, as well, most of the apparently puzzling positive relationship between momentum profits and market aggregate liquidity, which has been recently documented in the literature.

Appendices to Chapter 2

A. Turnover calculation

Following Barroso and Santa-Clara (2015), the monthly turnover, y_t, of each leg of the momentum strategy is given by:

$$y_t = 0.5 \times \sum_i^{N_t} \left| w_{i,t} - \widetilde{w}_{i,t-1} \right|, \tag{2.13}$$

where,

$$\widetilde{w}_{i,t-1} = \frac{w_{i,t-1}(1+r_{i,t})}{\sum_i^{N_t} w_{i,t-1}(1+r_{i,t})}, \tag{2.14}$$

$w_{i,t}$ is the weight of the stock i in the leg of the portfolio at time t , N_t is the number of stocks in the leg of the portfolio at time t, $r_{i,t}$ is the return on asset i at time t, and $\widetilde{w}_{i,t-1}$ is the weight of stock i the period right before trading. The turnover of the WML portfolio is the sum of the turnover of the short and the long legs.

B. Continuous and discrete uncertainty

Table 2.10
Continuous Uncertainty against Discrete Uncertainty

The table shows the results of a regression of WML portfolios, on market, size and value factors. It also presents the slopes of the regression including a the continuous EPU index, CONT.U., and an interaction effect between the continuous EPU index and the high economic uncertainty indicator.

	Continuous vs discrete uncertainty			
	b	*t(b)*	*b*	*t(b)*
ALPHA	2.81	5.55	1.25	1.80
RMRF	-0.39	-9.31	-0.39	-9.35
SMB	-0.19	-2.81	-0.20	-2.94
HML	-0.73	-12.14	-0.74	-12.31
CONT.U.	-0.01	-2.29	0.01	1.35
CONT.U. * H. UNC			-0.02	-3.27

C. Two legs of momentum

Table 2.11
Abnormal Returns of the Two Legs of the Winners minus Losers Portfolio

The table shows the results of a regression of the highest and lowest deciles of the portfolios, sorted according to prior performance, on market, size and value factors, and estimates for high economic uncertainty regimes, H. UNC (above 121.55 in the EPU index); an indicator variable for recessionary periods (REC); an indicator variable of whether the economy is in a high uncertainty regime and an expansion period, referred to as high good uncertainty (H. GOOD UNC); and, an indicator of whether the economy is in a recession and a high uncertainty regime, referred to as high bad uncertainty (H. BAD UNC). Finally, the table also shows the estimated slopes of an indicator that identifies episodes of recession and low uncertainty regimes (below the endogenous threshold), labeled as low bad uncertainty (L. BAD UNC). The impact of high uncertainty on the abnormal returns of momentum is in bold. The portfolio of losers was multiplied times minus one, as to ensure a short position. Newey–West (1987) adjusted standard errors were used to construct the reported t –statistics, *t(b)**.

	Short- Losers									
	b	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*
ALPHA	0.9	6.1	1.0	6.6	1.2	6.9	1.0	6.7	1.0	6.4
RMRF	-1.4	-49.7	-1.4	-49.9	-1.4	-49.9	-1.4	-50.0	-1.4	-49.9
SMB	-0.5	-10.5	-0.5	-10.5	-0.5	-10.6	-0.5	-10.6	-0.5	-10.6
HML	-0.4	-10.6	-0.4	-10.6	-0.4	-10.6	-0.4	-10.7	-0.4	-10.7
HIGH UNC.			-0.9	-2.6	-0.9	-2.5				
RECE.					-0.7	-1.9				
HIGH GOOD UNC							-0.5	-1.4		
HIGH BAD UNC							-2.2	-3.2	-2.2	-3.1
LOW BAD UNC									-0.3	-0.7

	Long- Winners									
	b	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*
ALPHA	0.9	9.2	1.1	10.4	1.2	10.0	1.1	10.4	1.0	8.9
RMRF	1.0	52.1	1.0	52.4	1.0	52.1	1.0	52.1	1.0	51.8
SMB	0.3	9.0	0.3	9.2	0.3	9.1	0.3	9.2	0.3	9.1
HML	-0.3	-10.7	-0.3	-10.8	-0.3	-10.8	-0.3	-10.9	-0.3	-10.9
HIGH UNC.			-1.1	-4.7	-1.1	-4.6				
RECE.					-0.3	-1.1				
HIGH GOOD UNC							-0.8	-3.1		
HIGH BAD UNC							-2.2	-4.5	-2.0	-4.2
LOW BAD UNC									0.2	0.6

D. Recent sample robustness:

Table 2.12

Momentum Abnormal Returns and Macroeconomic Uncertainty: 1992-2016

The table shows the results of a regression of WML returns on market, size and value factors and estimates of an indicator variable for high uncertainty regimes, H. UNC (above 70th, 80th, and 90th percentiles); an indicator for recessionary periods (REC), one for whether the economy is in a high uncertainty regime and an *expansion* period (H. GOOD UNC); and, an indicator of whether the economy is in a recession and a high uncertainty regime (H. BAD UNC). The table also shows the estimated slopes episodes of recession and low uncertainty regimes (L. BAD UNC). The impact of uncertainty on the abnormal returns is in bold.

					70th Percentile					
	b	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*
ALPHA	1.4	*3.0*	2.3	*3.7*	2.4	*3.9*	2.3	*3.8*	1.7	*3.4*
RMRF	-0.7	*-6.0*	-0.7	*-6.2*	-0.7	*-6.4*	-0.7	*-6.5*	-0.7	*-6.3*
SMB	0.2	*1.2*	0.2	*1.3*	0.2	*1.4*	0.2	*1.3*	0.2	*1.1*
HML	-0.5	*-3.5*	-0.6	*-3.7*	-0.6	*-3.7*	-0.6	*-3.8*	-0.6	*-3.7*
HIGH UNCERTAINTY			**-2.1**	*-2.2*	**-1.8**	*-1.9*				
RECE.					-2.1	*-1.3*				
HIGH GOOD UNC							-1.4	*-1.5*		
HIGH BAD UNC							-5.4	*-3.0*	-4.7	*-2.7*
LOW BAD UNC									4.5	*1.4*
					80th Percentile					
ALPHA	1.4	*3.0*	2.4	*4.3*	2.5	*4.5*	2.4	*4.4*	1.7	*3.6*
RMRF	-0.7	*-6.0*	-0.7	*-6.4*	-0.7	*-6.6*	-0.8	*-6.8*	-0.7	*-6.6*
SMB	0.2	*1.2*	0.2	*1.2*	0.2	*1.3*	0.2	*1.1*	0.1	*1.0*
HML	-0.5	*-3.5*	-0.6	*-3.8*	-0.6	*-3.9*	-0.6	*-4.1*	-0.6	*-4.1*
HIGH UNCERTAINTY			**-3.1**	*-3.1*	**-2.9**	*-3.0*				
RECE.					-2.2	*-1.4*				
HIGH GOOD UNC							-2.2	*-2.2*		
HIGH BAD UNC							-8.2	*-3.7*	-7.4	*-3.4*
LOW BAD UNC									1.7	*0.8*
					90th Percentile					
ALPHA	1.4	*3.0*	1.9	*3.7*	2.1	*3.9*	2.0	*3.9*	1.7	*3.6*
RMRF	-0.7	*-6.0*	-0.7	*-6.2*	-0.7	*-6.4*	-0.7	*-6.7*	-0.7	*-6.6*
SMB	0.2	*1.2*	0.2	*1.2*	0.2	*1.4*	0.2	*1.1*	0.1	*1.0*
HML	-0.5	*-3.5*	-0.6	*-3.7*	-0.6	*-3.7*	-0.6	*-4.2*	-0.7	*-4.2*
HIGH UNCERTAINTY			**-2.5**	*-2.2*	**-2.2**	*-1.9*				
RECE.					-2.3	*-1.4*				
HIGH GOOD UNC							-1.1	*-0.9*		
HIGH BAD UNC							-8.5	*-3.6*	-8.3	*-3.5*
LOW BAD UNC									1.2	*0.6*

Chapter 3: Measuring Uncertainty in the Stock Market

Abstract

We propose a daily index of time-varying stock market uncertainty. The index is constructed after first removing the common variations in the series, based on recent advances in the literature that emphasize the difference between risk (expected variation) and uncertainty (unexpected variation). To this end, we draw on data from 25 portfolios sorted by size and book-to-market value. This strategy considerably reduces information requirements and modeling design costs, compared to previous proposals. We compare our index with indicators of macro-uncertainty and estimate the impact of an uncertainty shock on the dynamics of macroeconomic variables. Our results show that, even when the estimates can be considered as a measure of financial uncertainty, they perform very well as indicators of the uncertainty of the economy as a whole.

4.2. Introduction

Uncertainty and risk have been primary concerns in economics, and among scientists in general, since the birth of modern science. Indeed, Bernstein (1998) goes as far as to claim that the interest in measuring and mastering the two phenomena marks the threshold separating modern times from the previous thousands of years of history.

In economics, Frank Knight was the first person to postulate the distinction between uncertainty and risk on the grounds that the former cannot be described by means of a probability measure while the latter can. According to both Knight (1921) and Keynes (1921, 1939), economic agents inhabit an environment of pervasive uncertainty and, therefore, there can be little hope of quantifying or forecasting economic variables, or of even taking informed decisions that rely on quantitative measures of economic dynamics (in other words, probabilities are incommensurable).

Today, the distinction between risk and uncertainty remains a lively topic for debate on the academic agenda. Indeed, several recent studies have attempted to explain decision- making under uncertainty, albeit oriented more towards the social conventions than towards the development of rational calculations. Accordingly, in this branch of the literature, there is a clear need to distinguish between the concepts, while measuring what can be measured and not losing sight of what cannot be quantified in probabilistic terms (Nelson and Katzenstein, 2014; Ganegoda and Evans, 2014; Taleb, 2007).

Although of obvious importance in its own right, this extreme *Knightian* differentiation between risk and uncertainty leads to the impossibility of defining a probability space and prevents us from using any variation of the Ergodic Theorem in empirical studies. And this, in turn, leads to the impossibility of conducting any science at all (Hendry, 1980; Petersen, 1996) or, at least, the kind of social science based on 'measurement', as has been fostered by the Cowles Commission for Research in Economics since its foundation[12].

However, confronted by this panorama, the profession has moved from this *Knightian* extreme (fundamental) view of uncertainty and adopted a more promising approach to the concept. In this new strand of the literature, uncertainty has generally been assimilated to a time-varying conditional second moment of the series under study, closely linked to underlying, time- varying, structural shocks, such as terrorist attacks, political events, economic crises, wars and credit crunches. Yet, despite this, the differentiation between risk and uncertainty in most instances is not properly dealt with.

Our contribution can be tough of as an attempt to measuring the 'known' and part of the 'unknown', in the popular taxonomy of risk proposed by Gomery (1995). This author differentiates between the 'known', the 'unknown' and the 'unknowable', and highlights a traditional exaggerated focus on the former, while ignoring the other two categories. That bias can lead to misconceptions about the world around us, because the 'known' constitutes only a very small fraction of what we see and face on our daily decisions. Nevertheless, there is still the 'unknowable', which is clearly beyond the scope of this paper, since in this situation even the events defining the probability space cannot be identified in advance as pointed out by Diebold et al. (2010).

In this paper we seek to make three specific contributions to the study of uncertainty. First, we propose a new index for measuring stock market uncertainty on a daily basis (or what we refer to as financial uncertainty). The index considers the inherent differentiation between uncertainty and the common variations between the series (which we identify as risk). Recent advances in the field have identified the methodological tools for performing the task using factor models (Jurado, Ludvigson and Ng, 2015; henceforth JLN). These proposals, however, have tended to focus their attention on the use of macroeconomic variables to construct their indexes, as opposed to financial variables. Therefore, because of the low frequency of macroeconomic series, the proposals lack a desirable property of traditional

[12] 'Science is Measurement' was the original motto of the Cowles Commission (though it would later be changed in 1952 to 'Theory and Measurement'). See Keuzenkamp (2004) and Bjerkholt (2014) for details about the history and methodology of econometrics and the role of the Cowles Commission and the Econometric Society in the transition of economics to a more formally based science.

proxies of uncertainty based on financial returns (such as VXO, VIX or credit-spreads): namely, practitioners and policy makers cannot trace their dynamics in real time.

Our second contribution is to show how our financial uncertainty index can also serve as an indicator of macroeconomic uncertainty. We examine the circumstances under which our index might be thought to capture all the relevant information in the economy as a whole. We exploit the fact that the information contained in hundreds, or even thousands, of economic indicators can be encapsulated by just a few stock market portfolio returns. This circumstance makes the construction of the index easier, in terms of its information requirements, modeling design and computational costs, and it allows us to provide a high frequency uncertainty measure. The construction of our index, based on portfolio returns, for which there are significant and timely data, provides a better basis for analyzing uncertainty compared to other situations, in which this kind of information and frequency are absent. Therefore, the extension of the methodology beyond the stock markets must be approached with caution, since there is little hope to extract the uncertainty components of less timely data, in an accurate fashion.

Finally, we analyze the dynamic relationship between uncertainty and the series of consumption, interest rates, production and stock market prices, among others. This allows us to further our understanding of the role of (financial or macroeconomic) uncertainty, and to determine the dynamics of the economy as a whole. Our empirical model allows us to analyze the extent to which traditional monetary policy can be trusted to manage situations of uncertainty. Thus, on the one hand, we document a significant and negative relationship between uncertainty and real variables such as production, employment and consumption; on the other, we find that the interest rate tends to decrease after an uncertainty shock while uncertainty decreases following a fall in the interest rate. However, this last effect only explains a small proportion of the total variation in the forecasted uncertainty.

The rest of this paper is organized as follows. First, we review theoretical and empirical studies of uncertainty. In section 3 we describe the methodology used to estimate the uncertainty index. Our approach relies on generalized dynamic factor models and stochastic volatility (SV) devices. In section 4 we present our data and in section 5 our main results. We also relate our findings to macroeconomic dynamics by means of a vector autoregressive (VAR) analysis. In the last section we conclude.

4.2. Related literature

A. Risk, uncertainty, economic decisions and policy intervention

The current paradigm for understanding uncertainty was developed within the framework of irreversible investment, in which a firm's future investment opportunities are treated as real options and the importance of waiting until the uncertainty is resolved is emphasized. Hence, aggregate uncertainty shocks[13] are thought to be followed by a reduction in investment, and possibly in labor, and, consequently, by a deterioration in real activity (Bernanke, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1996; Leahy and Whited, 1996; Caballero and Pindyck, 1996; Bloom et al., 2007; Bachmann and Bayer, 2013). Nevertheless, some studies point out that after the original worsening of the variables, a rebound effect related to a 'volatility over-shoot' may be observed (Bloom, 2009; Bloom et al., 2013). It is worth noting that these original impacts on the macroeconomic variables may be amplified as a result of financial market frictions (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014).

The study of uncertainty is not confined to the firm's investment problem. For example, Romer (1990) suggests that consumers may postpone their acquisition of durable goods in episodes of increasing uncertainty. Ramey and Ramey (1995) and Aghion et al. (2010) have studied the negative relationship between volatility and economic growth. The effects of uncertainty on equity prices and other financial variables have also been analyzed. In this stream, Bansal and Yaron (2004) provide a model in which markets dislike uncertainty and worse long-run growth prospects reduce equity prices. In the same line, Bekaert et al. (2009) find that uncertainty plays an important role in the term structure dynamics and that it is the main force behind the counter-cyclical volatility of asset returns.

Additionally, there has been a revival of interest in examining the relationship between uncertainty and policy interventions. However, there is no clear consensus in this resurgent research agenda. Some authors conclude that the optimal monetary policy does not change significantly during episodes of crisis and that uncertainty about crises has relatively little effect on policy transmission (Williams, 2012), but others report that financial uncertainty plays a significant role in monetary policy transmission mechanisms (Baum et al., 2013; Bekaert et al., 2013). Neither is it clear whether a highly responsive or moderate monetary policy scheme is best when facing uncertainty. For instance, Williams (2013), in the same spirit as Brainard (1967), forwards the argument that, once uncertainty is recognized, some moderation in monetary policy might well be optimal. In marked contrast (albeit under a different notion of uncertainty), Fendoğlu (2014) recommends a non-negligible response to uncertainty shocks.

[13] Panousi and Papanikolaou (2012) explain possible sources of inefficiency in the investment process arising from idiosyncratic uncertainty, under high-powered incentives and risk-averse managers. Bachmann and Bayer (2013) also study the impact of idiosyncratic uncertainty shocks on business cycles.

B. Empirical measures of uncertainty

Empirical studies have frequently relied on proxies of uncertainty, most of which have the advantage of being directly observable. Such proxies include stock returns or their implied/realized volatility (i.e., VIX or VXO), the cross-sectional dispersion of firms' profits (Bloom, 2009), estimated time-varying productivity (Bloom et al., 2013), the cross-sectional dispersion of survey-based forecasts (Dick et al., 2013; Bachmann et al., 2013), credit spreads (Fendoğlu, 2014), and the appearance of 'uncertainty-related' key words in the media (Baker et al., 2016).

Although these uncertainty proxies have provided key insights to the comprehension of uncertainty, and have been reliable starting points for the analysis of the economic impacts of uncertainty on economic variables, most of them have come under criticism, most notably from Scotti (2016) and JLN. On the one hand, volatility measures blend uncertainty with other notions (such as risk and risk-aversion), owing to the fact that they do not usually take the forecastable component of the variation into account before calculating uncertainty. On the other, analysts' forecasts are only available for a limited number of series. Moreover, it is not entirely clear whether the responses drawn from these surveys accurately capture the conditional expectations of the economy as a whole. The disagreement reported in survey forecasts could be more of an expression of different opinions than of real uncertainty (Diether et al., 2002) and even if forecasts are unbiased, the disagreement in analysts' point forecasts is not generally equivalent to forecast error uncertainty (Lahiri and Sheng, 2010) [14] . Aimed at overcoming these shortcomings, a new branch of the literature has emerged, which proposes measuring uncertainty only after the forecastable component of the series has been removed (Carriero et al., 2016[15]; Gilchrist et al., 2014; JLN).

Our model takes into account the extraction of the contemporaneously forecastable component of the variation before calculating uncertainty, which is important in order to distinguish satisfactorily between uncertainty and risk. We also aim to construct estimations of uncertainty by deliberately adopting an atheoretical approach, in the same vein as JLN. Our study contributes to the existing literature by providing a *daily* measurement of uncertainty. This is important, because it means the market can be monitored in real time, while enabling the researcher to undertake event studies with greater precision including uncertainty as a variable. The literature notes that estimations of

[14] Bachmann et al. (2013) and Scotti (2016) acknowledge these problems and address them by using additional proxies for uncertainty. Nevertheless, as noted by JLN, these studies focus on variation in outcomes around subjective survey expectations.

[15] These authors do not address the problem of measuring uncertainty directly, but still they use a closely related methodological approach to the one employed in this strand of the literature.

impacts extracted from event studies are much more precise and less noisy as the frequency of the data increases (Fair, 2002; Bomfim, 2003; Chuliá et al., 2010).

4.2. Methodology

The construction of our uncertainty index consists of two steps. First, we remove the common component of the series under study and calculate their idiosyncratic variation. To do this, we filter the original series using a generalized dynamic factor model (GDFM). Second, we calculate the stochastic volatility of each residual in the previous step using Markov chain Monte Carlo (MCMC) techniques. Then, we average the series, obtaining a single index of uncertainty for the stock market, and possibly for the economy as a whole. In sections 3.1 and 3.2 below, we explain each step in detail.

A. Idiosyncratic component extraction

Following Bai and Ng (2008), let N be the number of cross-sectional units and T be the number of time series observations. For $i = 1, \dots, N$ and $t = 1, \dots, T$, the dynamic factor model (DFM) can be defined as:

$$x_{it} = \lambda_i(L) f_t + e_{it}, \tag{3.1}$$

where $\lambda_i(L) = (1 - \lambda_{i1}L -, \dots, -\lambda_{is}L^S)$ is a vector of dynamic factor loadings of order s. When s is finite, we refer to it as a DFM. In contrast, a GDFM allows s to be infinite. Stock and Watson (2002, 2011) provide examples of the former and Forni and Reichlin (1998) and Forni et al. (2000) introduce the latter. In any case, the (dynamic) factors f_t evolve according to:

$$f_t = C(L)\varepsilon_t, \tag{3.2}$$

where ε_t are iid errors. The dimension of f_t, denoted q, is the same as that of ε_t and it refers to the number of dynamic or primitive factors (Bai and Ng, 2007).

The model stated in (3.2) can be rewritten in static form, simply by redefining the vector of factors to contain the dynamic factors and their lags, and the matrix of loads accordingly, as:

$$\underset{(N \times T)}{X} = \underset{(N \times r)(r \times T)}{\Lambda\, F} + \underset{(N \times T)}{e}, \tag{3.3}$$

where $X = (X_1, \dots, X_N)$ and $F = (F_1, \dots., F_T)$. Clearly, F and Λ are not separately identifiable. For any arbitrary $(r \times r)$ invertible matrix H, $F\Lambda' = FHH^{-1}\Lambda' = F^*\Lambda'^*$, where $F^* = F\Lambda$ and $\Lambda^* = \Lambda H^{-1}$, the factor model is observationally equivalent to $X = F^*\Lambda'^* + e$. Therefore r^2 restrictions are required to uniquely fix F and Λ (Bai and Wang, 2015). Note that the estimation of the factors by principal components (PC) or singular value decomposition (SVD) imposes the normalization that $\frac{\Lambda'\Lambda}{N} = I_r$ and $F'F$ is diagonal, which are sufficient to guarantee identification (up to a column sign variation).

The GDFM is a generalization of the DFM because it allows a richer dynamic structure for the factors. It places smaller weights on variables with larger idiosyncratic (uncertainty) components. So that the idiosyncratic 'error' contained in the linear combination is minimized. In this way we ensure that the uncertainty component is purged from risk-related variations.

Our first step enables us to estimate the idiosyncratic variation of the series $e_{it}^{u} = X_{it} - \hat{C}_{it}$, where $\hat{C}_{it} = \lambda_i(L)f_t$. This component is primarily related to uncertainty, whereas the common variation (i.e., the variance of $\hat{C}_{it}$) can be referred to as risk.

B. Conditional volatility estimation

Once we recover the series of filtered returns, e_{it}^{u}, a SV model is specified on an individual level, for each $i = 1, \dots N$[16], as:

$$e_t^u = e^{h_t/2}\epsilon_t, \tag{3.4}$$

$$h_t = \mu + \emptyset(h_{t-1} - \mu) + \sigma\eta_t \quad , \tag{3.5}$$

where ϵ_t and η_t are independent standard normal innovations for all t and s belonging to $\{1, \dots, T\}$. The non-observable process $h = (h_0, h_1, \dots, h_T)$ appearing in equation 3.5 is the time-varying volatility with initial state distribution $h_0|\mu, \phi, \sigma \sim N\left(\mu, \sigma^2/(1-\phi^2)\right)$. This centered parameterization of the model should be contrasted with the uncentered reparameterization provided by Kastner and Frühwirth-Schnatter (2014):

$$e_t^u \sim N\left(0, e^{\mu + \sigma \tilde{h}_t}\right), \tag{3.6}$$

$$\tilde{h}_t = \emptyset \tilde{h}_{t-1} + \eta_t, \ \eta_t \sim N(0,1). \tag{3.7}$$

Whether the first or the second parameterization is preferred for estimation purposes generally depends on the value of the 'true' parameters (Kastner and Frühwirth-Schnatter, 2014). Nevertheless, both of them have intractable likelihoods and, therefore, MCMC sampling techniques are required for Bayesian estimation.

Kastner and Frühwirth-Schnatter (2014) provide a strategy for overcoming the problem of efficiency loss due to an incorrect selection among the representations in applied problems. They propose interweaving (3.4)-(3.5) and (3.6)-(3.7) using the ancillarity-sufficiency interweaving strategy (ASIS) as

[16] In what follows we omit the cross-sectional subscript to simplify the notation.

introduced by Yu and Meng (2011). Their results indicate that this strategy provides a robustly efficient sampler that always outperforms the more efficient parameterization with respect to all parameters, at little extra cost in terms of design and computation. We follow their advice to estimate the volatilities of the idiosyncratic shocks.

Once the idiosyncratic stochastic volatility measures have been constructed, we are able to estimate the uncertainty index in the stock market as the simple average of the individual volatilities:

$$U_t = \frac{\sum_{i=1}^{N} h_{it}}{N}. \tag{3.8}$$

This scheme corresponds to the equally weighted average, with $\sum_{i=1}^{N} w_i h_{it} \overset{p}{\rightarrow} E(U_t)$, where $w = 1/N$. Alternatives, such as using the first PC to aggregate the series of variances, are possible but have no grounding in econometric theory to guarantee their consistency in the estimation process (Jurado et al., 2013; JLN). Unlike the previously referenced studies by JLN, here we only use information from portfolio returns organized by different factor criteria; thus, there is no *ex ante* reason to weight each portfolio return using different loads. In principle, any firm might belong to any portfolio, and all of them are equally important in the estimation of the aggregate shock. Hence, it is natural to favor the equally-weighted scheme over other asymmetric alternatives, but note that the asymmetric scheme would be more appropriate when macro-variables are blended with financial or other kind of variables.

4.2. Data

In our empirical exercise we use 25 portfolios of stocks belonging to the NYSE, AMEX, and NASDAQ, sorted according to size and their book-to-market value, as provided by Kenneth French on his website [17]. Those portfolios have been widely used in the literature examining multi-factor asset pricing models (Cochrane, 2005), and can be seen as a good summary of whole market dynamics. Moreover, Sentana (2004) justifies the use of portfolios for extracting the subjacent factors by proving that many portfolios converge to the factors as the number of assets increases. Clearly this does not rule out the fact that other possibilities might be explored in future research, such as the use of less well-known portfolios constructed on an industry sector basis, or using different factors to organize the series.

Our data set spans from 1 July 1926 to 30 September 2014, which gives a total of 23,321 observations. More details on the portfolio formation are provided in Davis, Fama and French (2000) and on Kenneth French's web page.

[17] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

In section 5.3 we estimate a vector autoregressive (VAR) model. The data for this exercise were taken from the web page of the Federal Reserve Saint Louis (FRED: http://research.stlouisfed.org/). Specifically, we use the Industrial Production Index; the total number of employees in the non-farm sector; Real Personal Consumption Expenditures in 2009 prices; the Personal Consumption Expenditures Price Index; the New Orders Index known as NAPM-NOI; Average Weekly Hours of Production and Nonsupervisory Employees for the Manufacturing sector (the all-sector index is not available from the beginning of our sample); Effective Federal Funds Rate; M2 Money Stock in billions of dollars and Standard and Poor's 500 index. Each series was taken seasonally adjusted where necessary, and the sample spans from February 1959 to September 2014, which is the longest period possible using these series.

4.2. Results

In this section we present our uncertainty index (section 5.1); we compare it with some of the main macro-uncertainty indicators (section 5.2); we analyze the relationship between our proposal and some real and financial variables, including policy variables (section 5.3); and, we perform several robustness exercises (section 5.4).

A. Uncertainty index

We estimate the GDFM using six static factors and one dynamic factor, which are optimal following the criteria proposed by Bai and Ng (2002) and Bai and Ng (2007), respectively. Based on these estimates we construct the uncertainty index by aggregating the conditional volatilities of the idiosyncratic residual series as explained in section 3.

The daily uncertainty index is presented in Figure 3.1, together with the recession dates in the United States, as indicated by the NBER on its web site. The index peaks coincide with well-documented episodes of uncertainty in the financial markets and the real economy, including the Great Depression, the recession of 1937-38 in the US, Black Monday in October 1987, the bursting of the dot-com bubble and the Great Recession 2007-2009.

Recession dates, such as August 1929 to March 1933, May 1937 to June 1938 and December 2007 to June 2009, clearly correlate with the amount of uncertainty in the market, although interestingly, not all recessionary episodes are preceded or followed by a notable uncertainty shock. For example, the uncertainty peak in the index corresponding to March 2000 appears one year before the economic contraction in March 2001. Likewise, several recessions during the decades of the 40s, 50s and 60s do not seem to be associated with episodes of high or even increasing uncertainty.

More importantly, uncertainty in the stock markets appears to correlate not only with the volatility of fundamentals (i.e., recessions), but also with episodes of over-valuation or bubbles in the market, as discussed for example in Yuhn et al. (2015), namely, those of 1987 (Black Monday), 2000 (information technology boom) and 2007 (housing market boom). Indeed, these episodes may well be the main drivers of uncertainty (even more so than the recessions), at least in the last part of our sample. Many such episodes have been identified in the recent literature and they constitute a particularly active area of current research within the financial econometrics field (Phillips and Yu, 2011; Phillips et al., 2011; Homm and Breitung, 2012; Phillips et al., 2015; Anderson and Brooks, 2014) and even outside economics, especially in the application of statistical mechanics tools to financial problems (see Zhou and Sornette (2003), Sornette and Zhou (2004), Sornette et al. (2009), Budinski-Petković et al. (2014) and references therein).

The observation above can be rationalized under a framework of agents with heterogeneous beliefs and bounded rationality as the one proposed by Hommes and Wagener (2009). In their model, there is an endogenous switching mechanism, governing the proportion of financial investors who follow a 'perfect foresight' forecasting rule (driven by market fundamentals), or alternative linear heuristics, such as 'biased beliefs' and 'past trends'. Instabilities may follow after an increasing in the number of non-fundamentalist traders in the market and hence, produce the apparition of persistent bubbles. Uncertainty, as measured by our index, is naturally related to this possibility. That is, in high uncertainty regimes more agents may choose to switch to a non-fundamentalist rule of prediction, driving the prices away from their fundamental path.

In Table 3.1 we report descriptive statistics for a monthly (end-of-the-month) version of the uncertainty index. We construct this monthly index to facilitate comparisons with other macro-uncertainty proxies. The skewness, kurtosis, persistence and half-life of the shocks for the full sample and for two sub-samples are presented (January 1927 to March 1940 and April 1940 to September 2014). This break date was chosen after testing for multiple breaks (Bai and Perron, 1998, 2003) in the autoregressive model of the shocks persistence (AR(1) with drift)[18].

[18] See Perron (2006) for a survey of this literature.

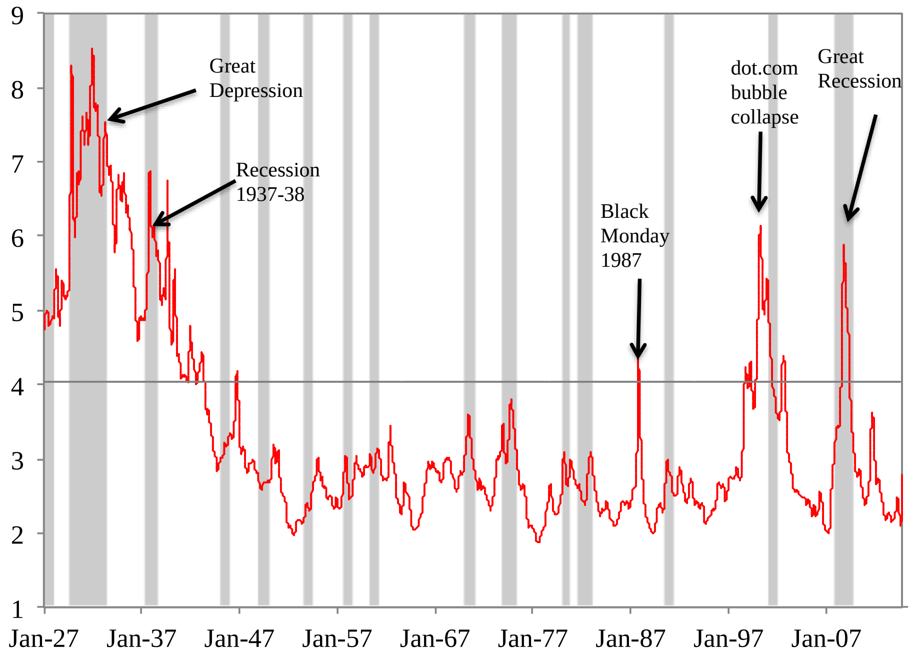

Figure 3.1: Uncertainty Index: Jan-06-27 to Sept-30-14. The first 153 observations have been discarded and the last 153 have been replaced by calculations using a (scaled) one-sided filter version of the GDFM (Forni et al., 2005). The reason for doing this is that original GDFM are biased at the beginning and at the end of the sample, because they make use of the estimation of the variance- covariance matrices of order $\sqrt{T}$. Grey areas correspond to NBER recession dates (peak-to-trough), including the peaks and troughs. The horizontal line corresponds to the 95 percentile of the empirical distribution of the index from Jan-40 onwards. The original measure is rescaled by a factor of 100 in the plot.

Table 3.1. Summary statistics of the uncertainty index in two sub-samples

	Sample period		
Statistic	Jan 1927-Sept 2014	Jan 1927-Mar 1940	Apr 1940-Sept 2014
Skewness	1.60	0.32	1.70
Kurtosis	4.74	1.97	6.62
Persistence, AR(1)	0.993	0.963	0.978
Half-life: months (years)	101 (8.42)	18.3 (1.53)	31.9 (2.65)

Table 3.1 shows that using the full sample to calculate persistence can lead to a spurious estimation of the summary statistics. Indeed, the sample distribution

of the uncertainty index in the two sub-samples looks quite distinct. In the first part of the sample, persistence is smaller and, therefore, the 'shocks' disappear in a shorter period of time (1.53 years) than is the case in the second sub-sample (2.65 years). There are fewer observations distant from the mean and, lastly, the distribution presents a slightly asymmetric behavior (skewness equal to 0.32). In contrast, even when the second part of the estimation presents shocks of a smaller magnitude (Figure 3.1), the distribution that characterizes them tends to generate a higher number of 'outliers' (kurtosis equal to 6.92) and they are more likely to be above than below the mean (1.7 is the asymmetric coefficient). This behavior may be interpreted as uncertainty showing some degree of inconsistency across time, which is related to the knightian framework, for which uncertainty is indeed understood as a non-predictable state.

Our estimations of persistence of macro-uncertainty are lower than those reported elsewhere, for example, those provided by JLN. The latter estimate a persistence of 53.58 months, while in the second part of our sample our estimation is of 31.9 months (41.2 months from Jan. 1960 to Sept. 2014). This could be interpreted as evidence that financial-uncertainty shocks are not as persistent as macro-uncertainty shocks. Nevertheless, it should be noted that JLN also report the persistence and half-lives of frequently used proxies for uncertainty, including the VXO and the cross-sectional standard deviation of the returns. They show that these uncertainty-related measures are far less persistent than are macro-uncertainty shocks (with half-lives of 4.13 and 1.92 months). Thus, the half-life and persistence of our uncertainty measure are more similar to those of the macro-uncertainty shocks than to those derived from the volatility measures.

B. Correlations with macro-uncertainty indexes

The closest measure of uncertainty to ours, methodologically speaking, is the uncertainty index proposed by JLN, although their proposal might be interpreted more directly as a 'macro-uncertainty' indicator, given its emphasis on economic variables as opposed to purely financial ones. Given these circumstances, it seems to be a good candidate with which to compare our index while seeking to identify any convergent and divergent paths. In order to compare the indexes, we first reduce our sample to fit theirs. Our resampled data start in January 1960 and end in May 2013[19]. After so doing, we recalculate our uncertainty index by aiming to use the same dates as those employed by JLN. Second, we take the end-of-the-month value of our index, to resemble their index frequency (monthly).

The results are reported in Figure 3.2. The shaded areas in the plot correspond to periods of 'high' correlation. The Pearson's correlation for the full sample between the indexes is barely above 22%, which could be interpreted, at first glance, to indicate that different forces lie behind the macro-uncertainty and the financial-uncertainty. However, this correlation seems very volatile. We also calculate moving-window correlations of five years during the sample and here our findings are more informative than the static correlation. The correlation remains above 50% for most of the period (left panel). Moreover, for the last part of the sample (from around February 2009 to May 2013), this correlation remained above 90%, revealing practically no difference in the indexes' dynamics. Even higher values were reached during the 70s and we observe correlations between 40 and 80% in the period from May 1994 to February 2003 (right panel). There are also two periods in which this correlation became negative, specifically from January 1992 to August 1993 and December 2005 to September 2007. After these short phases, the indexes started to move in the same direction once again, and in both cases with a stronger impetus than before.

Finally, an analysis of the levels of the uncertainty indexes shows them to be particularly different during the periods from March 1979 to May 1983 and July 1998 to January 2003. Our intuition regarding the explanation for these divergent paths during these periods is that while uncertainty in the financial markets is driven significantly by bubble episodes, such episodes are not always the drivers of the recessions in the real economy and, therefore, cannot be related on a one-to-one basis with macro-uncertainty. Thus, the financial-uncertainty index highlights uncertainty associated with bubble episodes (for instance, during the dot.com collapse) that did not materialize as strong recessionary phases in the real economy and which, therefore, are not captured by the JLN-uncertainty index. In the same vein, recessionary episodes not directly related to the financial market (such as those from 1979 to 1983) are not especially pronounced in our financial-uncertainty indicator.

[19] The JLN-index is publicly available for this period on Sidney Ludvigson's web page: http://www.econ.nyu.edu/user/ludvigsons/

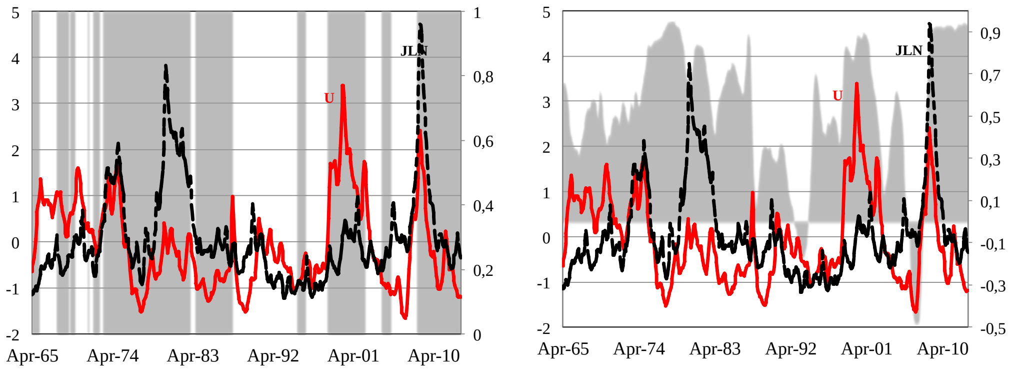

Figure 3.2: Uncertainty Comparisons I. The solid line represents our Uncertainty Index (U), while the dotted line represents the Jurado-Ludvigson-Ng's Index (JLN) with forecast horizon $h = 1$, both from Apr-65 to May-13. In the panel on the left, the shaded areas correspond to correlation periods above 0.5. In the panel on the right, the shaded areas are the actual correlations. Correlations were calculated using rolling windows of five years.

We also compare our index with the VIX, another frequent proxy for macro- and financial-uncertainty (Figure 3.3), but which is only available after January 1990. We found a correlation of 65.2% using the full sample. The dynamics of the VIX and the uncertainty index appear to be largely similar with a correlation above 70% for the last ten years of the sample. However, these dynamics are considerably different (considering the correlation levels) for the first ten years of the sample. Here again, the results could be linked to the fact that volatility as a risk measure is inversely related to the presence of over-valuation in the stock markets, whereas over-valuation appears to be positively related to uncertainty.

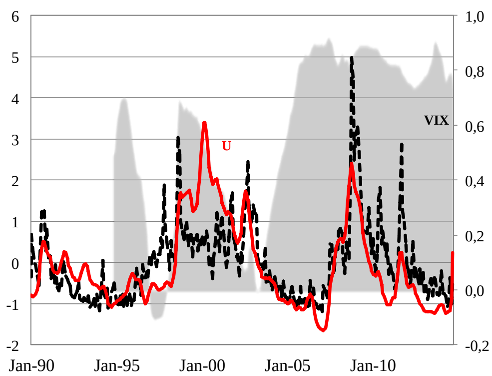

Figure 3.3: Uncertainty Comparisons II. The solid line represents our uncertainty index (U), while the dotted line represents the VIX, both from Jan-90 to Sept-14. Shaded areas correspond to the five-year rolling correlations and, therefore, start only after Jan-95. Correlations are measured along the right axis.

C. VAR dynamics: Uncertainty, economic activity and policy variables

In this section, we explore the dynamic relationship between our uncertainty index and some macroeconomic and financial variables. To do so, we use the model proposed by Christiano et al. (2005). This model has been widely studied in the literature and is, therefore, useful for comparing our uncertainty estimates. The model is given in reduced form by:

$$Y_t = A(L)Y_{t-1} + e_t, \tag{3.9}$$

where, $Y_t = [Y_{1t}\ , R\ , Y_{2t}, U\ ]'$ is a matrix $(T \times N)$ containing the N column-vectors of the model. Y_{1t} contains slow-moving variables which do not react contemporaneously to a monetary policy shock: Production, Employment, Consumption, Inflation, New Orders, Wages and Labor. R refers to the Federal Funds Rate, understood as the monetary policy instrument. Y_{2t} refers to the fastest variables, which are assumed to respond contemporaneously to the policy innovation, such as: the Stock Market Index and M2. Finally, we place our Uncertainty Index U in last position (as do JLN and Bloom, 2009)[20]. We estimate a VAR with 12 lags, as opposed to the four quarters used in Christiano et al. (2005) to cover the same time-span. All the variables enter in log-levels, with the exceptions of the Federal Funds Rate and Uncertainty, which enter in original units, and M2, which enters in growth rates. We recover the structural innovations by means of a Cholesky factorization of the variance-covariance matrix. As is well known, the Cholesky decomposition implies a certain ordering of the set of variables, depending on whether they react or not to other variables contemporaneously. Following Christiano et al. (2005), the variables are sorted from more exogenous to more endogenous as stated above. The impulse response functions are presented in Figure 3.4.

The reactions of Production and Employment to uncertainty shocks have been studied elsewhere, for example in JLN and Bloom (2009). The former report very similar results to ours even when using their uncertainty index, which requires considerably more information, processing time and modeling design than are required by our index (see also section 5.4). Production reacts negatively to uncertainty increments and the persistence of the shock extends beyond the two-year horizon. In the sixth months after the innovation, 10.5% of the forecast error of the production series is explained by the uncertainty

[20] See section 3.4 for a more detailed description of the data used in this section.

shock, and up to 23.8% is explained 12 months on[21].

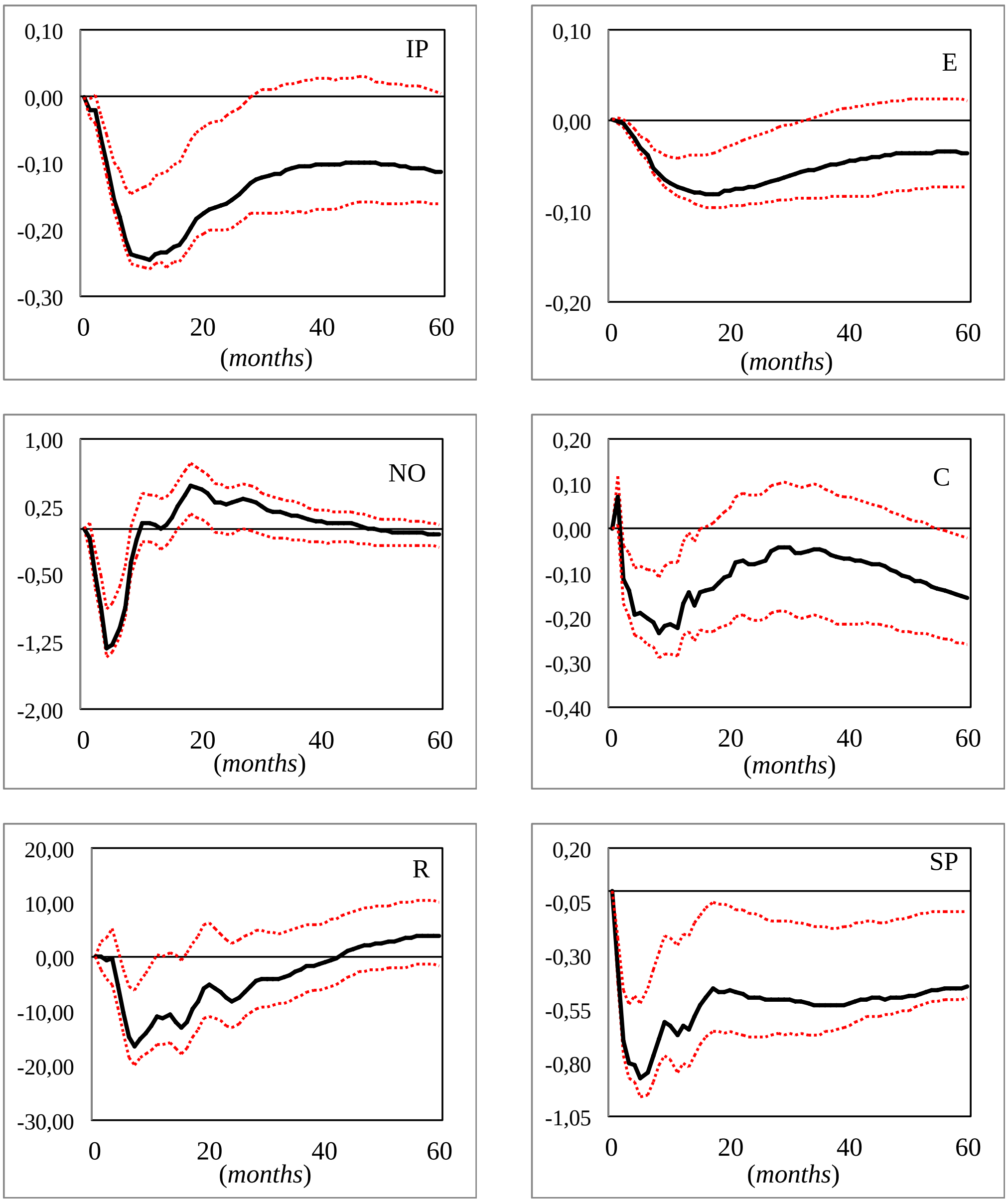

Figure 3.4: Economic Dynamics under Uncertainty. We use a VAR (12) comprising 11 variables. The axes are in percentages but the Federal Funds Rate is in basic points. The figure shows the reaction of the variables to an unexpected increment of uncertainty. The estimation period runs from February 1959 to September 2014. Confidence bands (86%) are calculated using bootstrapping techniques as explained in Efron and Tibshirani (1993). The variables are defined as: IP: Industrial Production Index, E: Employment, NO: New Orders, C: Consumption, R: Federal Funds Rate, SP: Standard and Poor's 500.

[21] See Table 3.2 in the Appendix.

Analogously, although at a smaller magnitude, employment decreases following a positive uncertainty shock and the impact persists for two and a half years (that is, six months more than in the case of production)[22]. Neither we nor JLN find any evidence supporting the 'rebound' effect proposed by Bloom (2009) in the case of production. However, the rebound effect is evident when analyzing the New Orders variable, which is a better proxy for current investment. First, new orders decrease in the face of uncertainty – a negative impact that lasts approximately eight months, but there is a statistically significant rebound effect in months 16 to 19. The reason why a similar effect is not detected in the production dynamics could be that following the original uncertainty shocks, negative feedback is obtained from consumption and expected demand.

Although there are theoretical claims explicitly linking uncertainty shocks and consumption (see, for instance, Romer, 1990), little empirical evidence has been presented to document this relationship. Here, we find that after an increment in uncertainty, consumption is severely affected (indeed, more or less in the same proportion as production, and more so than employment). However, the shock tends to disappear more quickly (1.3 years before the upper confidence band reaches zero), but it is also apparent that it causes the series to stabilize at a lower level relative to that of the production series.

In line with the theory, financial prices, such as the stock market index, are significantly affected by uncertainty in the financial markets. Indeed, the marked fall in the market index in the face of uncertainty, and the stabilization of the sequence at a lower level, is consistent with the theoretical discussion in Bansal and Yaron (2004). Basically, the intuition is tied to the fact that markets do not like uncertainty and after an increase in uncertainty, the discount of the expected cash flows is greater, causing the market to reduce the price of the stock.

As can be seen from Table 3.2 in the Appendix, a variance decomposition of the forecast errors of the series confirms the importance of uncertainty as a driver of the economy's dynamics. One year after the original structural innovation, it accounts for 23.8% of the variance in production, 19.5% of new

[22] JLN report an impact of their uncertainty shock on production that persists for more than 60 months. We also find that the IRF tends to stabilize at a lower level following a shock, as can be seen in Figure 3.4, although this is only true for the average level. Note that the bootstrapped confidence intervals of our exercise prevent us from fixing the effects beyond three years as statistically different from zero.

orders, 13.2% of employment and 15.9% of the stock market prices. In all cases, it is the second or third largest source of variation. It also affects other series, albeit to a lesser degree, including consumption (7.6%) and Federal Funds (4.7%), being in these cases the fourth or fifth cause of variation among the eleven variables considered.

Lastly, the Federal Funds Rate also seems to be sensitive to uncertainty. In the face of an uncertainty shock the Federal Reserve tends to reduce the interest rate (thereby confirming that the reduction in equity prices is due to uncertainty and not to possible confounding interest movements). The reduction is particularly persistent during the first year before it begins to disappear. Nevertheless, the uncertainty shock only accounts for between 4 and 5% of the total variation in the Fed rate according to the variance decomposition.

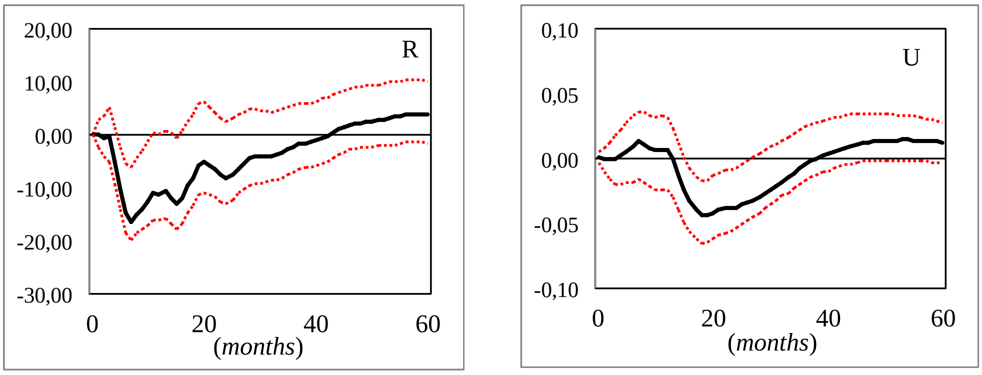

Figure 3.5: Policy intervention and uncertainty. We use a VAR (12) comprising 11 variables. The axes are in basic points and units, respectively. We replicate the left panel from Figure 3.5 and we multiply by minus one the response to an increase in the Federal Funds Rate, to be consistent with the text. The estimation period runs from February 1959 to September 2014. Confidence bands (86%) are calculated using bootstrapping techniques as explained in Efron and Tibshirani (1993).

The Cholesky identification strategy allows us to distinguish the effect in the reverse direction; in other words, it enables us to answer the question: Does an expansionary monetary policy decrease uncertainty? As can be observed in Figure 3.5, a loosening monetary policy does affect uncertainty. The effects are expected to occur with a lag of one year, to last for a further year, and after this period, to disappear. This finding is in line with similar effects documented by Bekaert et al. (2013), although they use non-corrected uncertainty measures and an alternative strategy to differentiate it from risk.

Our results in this direction add to the research field by exploring the relationship between policy intervention and uncertainty. However, the effects are small in magnitude (see Table 3.2 in the Appendix), with between 2 and 6% being due to the monetary policy innovations.

Finally, in Figure 3.6, using our proposed index and JLN's index, we compare the responses of the variables facing uncertainty. However, the qualitative and quantitative results reported above do not vary significantly depending on the uncertainty measure used.

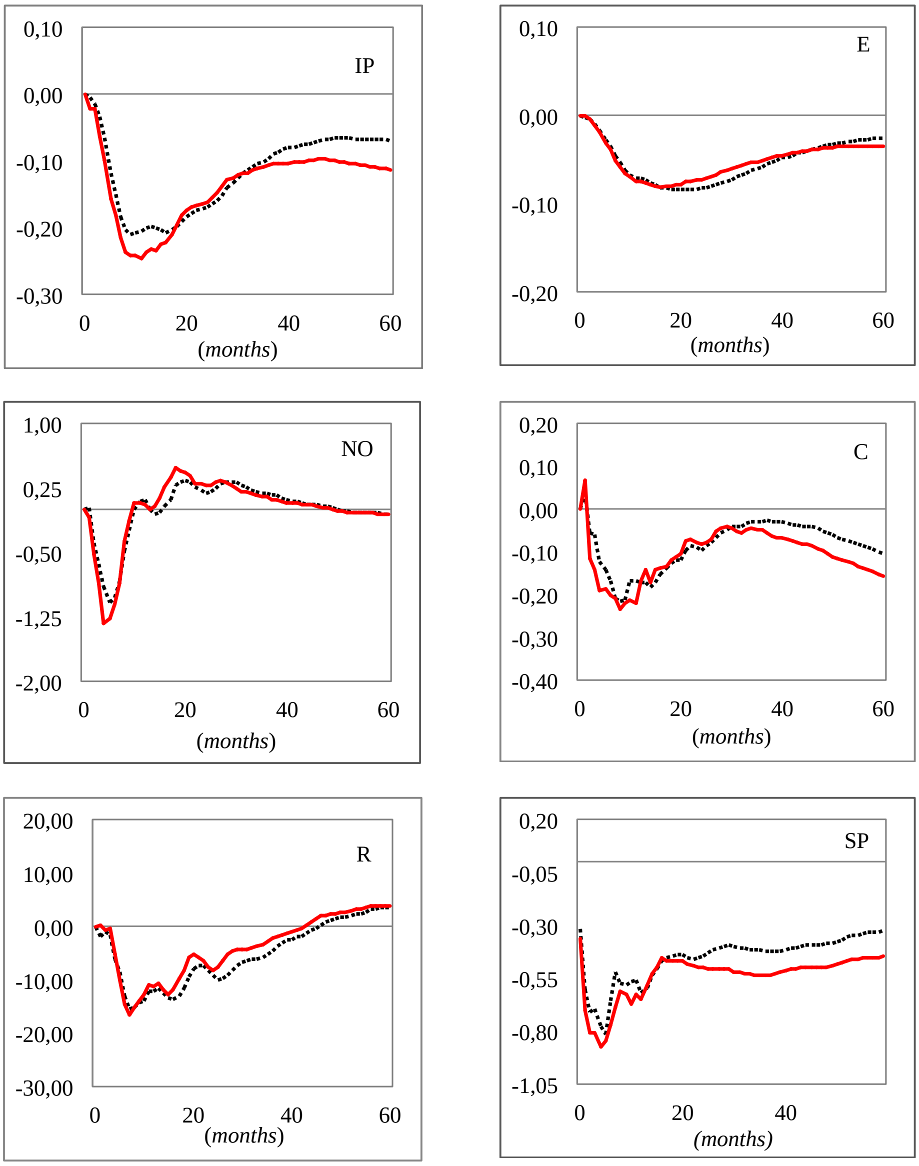

Figure 3.6: Economic Dynamics under Uncertainty. Comparison of the JLN and U Indexes. We use a VAR (12) comprising 11 variables. The figure displays the reaction of the variables to an unexpected increment in two standardized uncertainty measures, the U index

(solid line) and the JLN index (dotted line). The estimation period for the U index runs from February 1959 to September 2014 whereas the JLN index is only publicly available from July 1960 to May 2013 on one of its author's web pages; therefore, we use this latter period to estimate the IRFs in this case. The variables are defined as: IP: Industrial Production Index, E: Employment, NO: New Orders, C: Consumption, R: Federal Funds Rate, SP: SP500.

4.2. Robustness

We perform several robustness exercises varying the econometric methodology employed to extract the idiosyncratic component.

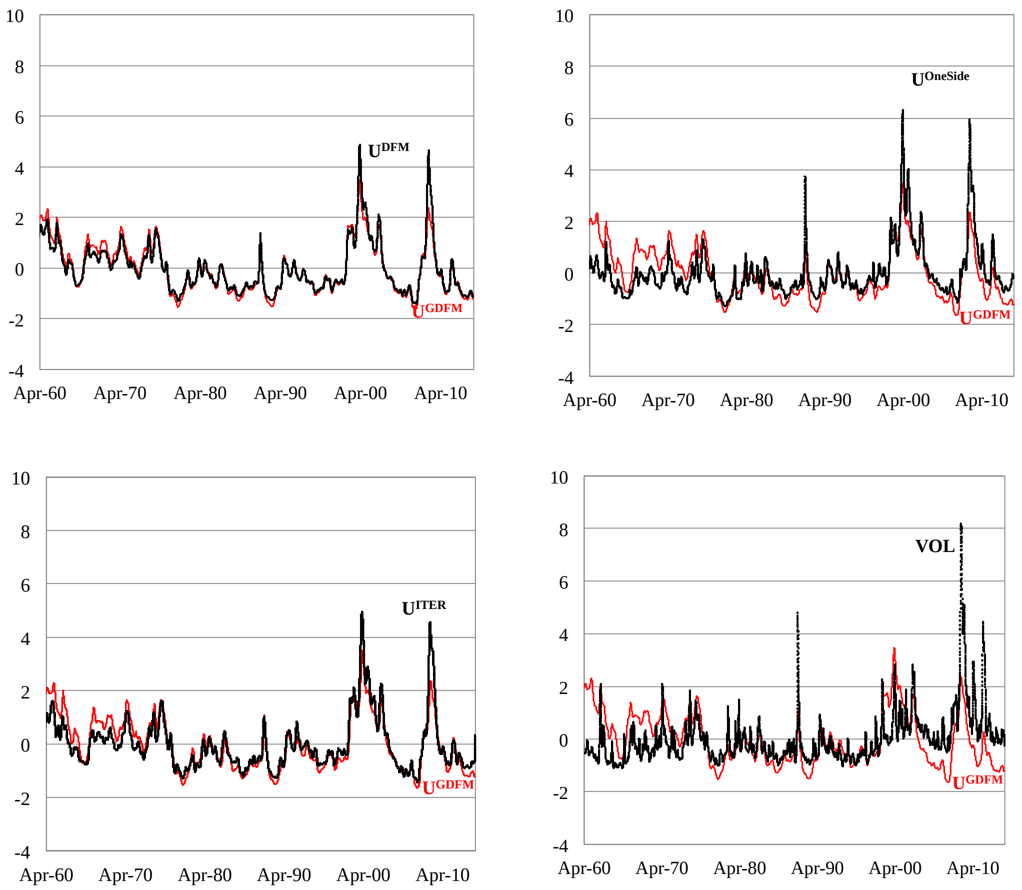

Figure 3.7: Robustness exercises. The uncertainty index using GDFM (solid line) is compared with different alternatives: a DFM (top left), a one-sided filter version of the GDFM (top right), a recursive algorithm (bottom left) and a conditional volatility measure of the original series (bottom right). All the indexes have been standardized to make proper comparisons.

We estimate the uncertainty index using DFM instead of GDFM; we also use the 'one-sided' filter version of the GDFM proposed by Forni et al. (2005) as opposed to the two-sided original GDFM, for the full sample; we estimate the index as the stochastic volatility without using any factor model to extract the idiosyncratic component and, finally, we estimate the idiosyncratic component in a recursive fashion, recalculating each model with rolling windows of 80 days (approx. one quarter). The latter approach speaks directly about parameter stability. The main results are summarized in Figure 3.7.

In general the uncertainty index behaves in a very similar fashion, regardless of the factor methodology used to extract the idiosyncratic components of the series. Nor does it change when we use recursive estimations. Nevertheless, its behavior is considerably different to that of the stochastic volatility of the original series. This, however, is not surprising and is indeed in-line with previous findings in the literature. Volatility measures tend to overestimate the uncertainty of the economy because they confuse uncertainty with risk or risk aversion.

4.2. Conclusions

We propose an index of time-varying financial uncertainty. The construction of this index is relatively simple as it does not rely on excessive data mining devices nor does it have to satisfy demanding information requirements. We construct the index on a daily basis, for the United States' economy between 1927 and 2014. As such, the index can be used to perform event studies, that is, to evaluate the impact of policy treatments on economic uncertainty, thanks to the higher frequency it offers compared to other proposals.

Our estimations allow us to identify several periods of uncertainty, some of which coincide with well-documented episodes, including major recessions, wars, and political upheavals. Others, especially those occurring in more recent decades, are more closely associated with bubble regimes in the stock market. We also document a change in the persistence of uncertainty between 1940 and 2014 compared to that recorded between 1927 and 1940. Current uncertainty is more persistent and is plagued with more extreme observations, although current periods tend to be smaller in magnitude than earlier periods.

We discuss the circumstances under which our index is a better measure of financial uncertainty and when it is in agreement with measures available elsewhere. We conclude that significant departures between macro-uncertainty and financial uncertainty can be expected during bubble episodes and we present evidence of this.

However, the economic dynamics that we document here (using a VAR model) are consistent with theoretical expectations and previous empirical studies (when available). For example, we find that after an uncertainty shock, production and employment react negatively and the effects of the shock tend to disappear slowly. We also present novel empirical evidence regarding the negative effect of uncertainty on consumption, inventory investment (including overshooting) and stock market prices.

Finally, we explore the relationship between uncertainty and policy variables. We find that there is indeed a relation between the reference interest rate in the economy and uncertainty. The interest rate tends to decrease in the face of an uncertainty shock, while the uncertainty shock decreases following a loosening of the monetary policy position, with a lag of one-year. However, this latter effect is very small in terms of accounting for the total variation of the forecast errors of the uncertainty variable. This result raises questions regarding the capability of the central banks to combat uncertainty by means of traditional monetary policy.

Appendix to Chapter 3

In the estimations we make use of some routines from the web page of Serena Ng (http://www.columbia.edu/~sn2294/) to estimate the DFM, and to select the optimal number of static and dynamic factors. To estimate the GDFM, both, one-side and two-sides filters, we use codes from the web page of Mario Forni. (http://morgana.unimore.it/forni_mario/matlab.htm). To estimate stochastic volatilities we use the r-package 'stochvol' (Kastner, 2016), to estimate structural breaks in the index we employ the r-package 'strucchange' and to estimate the VAR model the r-package 'vars' was used.

Table 3.2: Variance Decomposition of the Forecast Errors

	Industrial Production					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	95.2%	68.2%	41.8%	23.7%	16.8%	95.2%
Employment	0.7%	3.6%	3.2%	2.1%	5.3%	7.1%
Consumption	0.1%	0.2%	1.0%	0.8%	1.7%	2.2%
Inflation	0.3%	0.2%	2.4%	15.4%	17.0%	18.7%
New Orders	2.5%	8.1%	4.6%	4.9%	3.6%	8.2%
Wage	0.0%	0.1%	0.2%	0.5%	1.0%	1.1%
Hours	0.8%	0.6%	0.4%	0.7%	0.4%	0.9%
R	0.0%	1.6%	4.5%	12.8%	26.0%	26.3%
S&P500	0.0%	5.0%	11.8%	9.8%	6.8%	13.7%
M2	0.0%	1.8%	6.3%	7.7%	7.7%	7.9%
Uncertainty	0.3%	10.5%	23.8%	21.7%	13.7%	25.3%

	New Orders					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	10.9%	7.5%	8.4%	7.7%	7.3%	10.9%
Employment	3.1%	5.3%	5.9%	5.4%	5.0%	6.1%
Consumption	2.9%	1.9%	1.8%	1.5%	1.4%	3.1%
Inflation	1.9%	2.7%	9.2%	12.6%	12.6%	12.8%
New Orders	78.7%	48.2%	39.9%	33.8%	31.5%	78.7%
Wage	0.0%	0.3%	0.4%	0.5%	0.5%	0.5%
Hours	0.5%	0.8%	1.7%	1.5%	1.5%	1.7%
R	0.0%	5.7%	7.2%	8.8%	9.7%	10.5%
S&P500	1.6%	4.9%	4.5%	10.5%	12.7%	13.3%
M2	0.2%	1.2%	1.5%	1.4%	1.4%	1.6%
Uncertainty	0.1%	21.5%	19.5%	16.4%	16.4%	22.6%

	Consumption					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	2.9%	5.3%	3.9%	2.1%	1.7%	6.7%
Employment	0.7%	4.8%	3.5%	1.8%	3.4%	5.3%
Consumption	93.8%	62.7%	45.0%	31.9%	25.4%	93.8%
Inflation	0.6%	6.4%	14.4%	24.3%	25.4%	26.1%
New Orders	0.3%	0.8%	2.1%	5.0%	4.8%	5.2%
Wage	0.0%	0.3%	0.4%	0.3%	0.4%	0.4%
Hours	0.0%	0.8%	1.0%	0.9%	0.7%	1.1%
R	0.5%	7.4%	12.1%	19.0%	23.6%	23.8%
S&P500	0.7%	3.9%	4.8%	3.3%	2.1%	5.0%
M2	0.2%	2.3%	5.1%	6.6%	9.5%	10.8%
Uncertainty	0.3%	5.3%	7.6%	4.7%	3.1%	7.8%

	Employment					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	32.8%	29.5%	19.1%	11.8%	8.8%	35.1%
Employment	66.1%	53.2%	42.5%	26.3%	11.5%	66.1%
Consumption	0.1%	0.6%	0.4%	0.5%	0.3%	0.8%
Inflation	0.0%	0.1%	0.8%	9.0%	13.3%	14.1%
New Orders	0.7%	4.4%	2.3%	1.9%	2.0%	4.5%
Wage	0.1%	0.1%	0.3%	0.8%	1.4%	1.4%
Hours	0.1%	0.1%	0.4%	1.8%	2.2%	2.3%
R	0.0%	2.5%	7.4%	19.6%	41.4%	44.5%
S&P500	0.1%	3.9%	10.4%	9.2%	7.5%	12.5%
M2	0.0%	0.9%	3.3%	4.2%	3.4%	4.2%
Uncertainty	0.0%	4.6%	13.2%	14.7%	8.2%	15.5%

	Standard & Poor's 500					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	0.3%	0.5%	0.4%	0.5%	1.2%	1.2%
Employment	0.1%	1.3%	2.7%	4.1%	5.6%	6.2%
Consumption	0.3%	0.9%	1.8%	1.8%	1.6%	1.8%
Inflation	0.5%	0.4%	4.0%	6.9%	5.8%	6.9%
New Orders	0.3%	1.3%	3.8%	5.7%	4.6%	5.7%
Wage	0.0%	0.2%	2.2%	4.3%	8.0%	9.0%
Hours	0.6%	1.0%	0.8%	0.9%	1.0%	1.0%
R	1.0%	1.5%	1.1%	1.2%	2.1%	2.1%
S&P500	94.5%	73.6%	63.6%	54.1%	44.7%	94.5%
M2	0.2%	3.4%	3.6%	3.9%	3.7%	4.0%
Uncertainty	2.2%	15.9%	15.9%	16.7%	21.7%	23.4%

	Federal Funds -R					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	0.0%	6.4%	5.4%	4.9%	6.2%	6.5%
Employment	0.0%	1.7%	6.5%	8.6%	8.2%	9.1%
Consumption	0.0%	0.5%	2.5%	3.3%	8.5%	11.0%
Inflation	0.0%	2.2%	3.7%	3.5%	4.0%	4.0%
New Orders	0.0%	10.6%	11.2%	9.2%	7.6%	11.2%
Wage	0.0%	0.8%	0.7%	0.8%	0.8%	0.9%
Hours	0.0%	1.0%	1.1%	1.1%	1.3%	1.3%
R	0.0%	72.8%	55.9%	47.8%	42.2%	91.7%
S&P500	0.0%	1.7%	6.8%	13.3%	14.4%	16.9%
M2	0.0%	0.5%	1.6%	1.7%	1.5%	1.7%
Uncertainty	0.0%	1.9%	4.7%	5.9%	5.4%	6.1%

	Uncertainty					
Period	**1**	**6**	**12**	**24**	**48**	**Max**
Ind. Production	0.5%	1.9%	2.4%	2.0%	2.2%	2.4%
Employment	0.1%	0.8%	1.0%	1.4%	1.2%	1.5%
Consumption	0.0%	0.5%	1.6%	1.3%	1.1%	1.6%
Inflation	0.4%	2.6%	5.9%	4.8%	5.6%	6.0%
New Orders	0.1%	0.3%	0.4%	1.0%	2.0%	2.1%
Wage	0.0%	0.7%	3.7%	3.5%	3.3%	4.3%
Hours	0.0%	0.7%	1.4%	1.9%	2.2%	2.2%
R	0.0%	0.1%	0.2%	4.0%	4.8%	5.0%
S&P500	1.3%	3.8%	7.1%	22.6%	28.2%	28.6%
M2	1.8%	3.1%	3.1%	2.6%	3.3%	3.4%
Uncertainty	95.7%	85.6%	73.2%	54.9%	46.1%	95.7%

NOTE: We use a VAR (12) comprising 11 variables, in the following Cholesky-order Production, Employment, Consumption, Inflation, NO, Wages, Labor, R (Federal Funds Rate), Stock Market Index, M2 and the Uncertainty Index.

Chapter 4: Uncertainty, Systemic Shocks and the Global Banking Sector: Has the Crisis Modified their Relationship?

Abstract

We estimate the impact of equity market uncertainty and an unobservable systemic risk factor on the returns of the major banks in the global banking sector. Our estimation combines quantile regressions, structural changes, and factor models and allows us to explore the stability of systemic risk propagation among financial institutions. We find that risk propagation has remained stable over the last decade, and we report evidence indicating that equity market uncertainty is a major factor for the global banking system. Additionally, we provide a new simple tool for measuring the resilience of financial institutions to systemic shocks.

4.1. Introduction

Systemic risk can be defined as the risk that a financial institution faces during periods of widespread financial distress, following exposure to an extreme negative shock in the market. This shock may arise either as a consequence of the failure of an individual firm of sufficient size and connectedness that it imposes significant marginal distress costs on the rest of the system, or as a common shock to the financial structure that is absorbed and amplified by various firms depending on their own particular resilience (Jobst, 2014a). The materialization of systemic risk may lead to disruptions in the provision of key financial services due to impairments of all or parts of the financial system, which may in turn have adverse consequences for the functioning of the real economy (see Acharya et al., 2017, and Adrian and Brunnermeier, 2014).

For these reasons, in recent years systemic risk has become a growing concern for regulators, who have made great efforts not only to measure the impact of systemic risk on individual firms, but also to identify systemically important financial institutions (SIFIs) that should adhere to stronger capital requirements to avoid giving rise to shocks which might destabilize the whole system. As a result, significant advances have been made in systemic risk regulation, as documented by both the Financial Stability Board (FSB) and the International Association of Insurance Supervisors (IAIS).[23]

[23] See for example FSB (2011, 2012, 2013) and IAIS (2009, 2012, 2013).

Several methodologies have been proposed for measuring systemic risk, above all in the banking sector.[24] The most common seek to estimate marginal increments in the value-at-risk statistics (VaR) of financial institutions, or increments in the marginal expected shortfall (ESF) of each firm, under a scenario of financial turmoil.[25] The reason for focusing on a financial institution's VaR or ESF is because extreme negative scenarios are naturally related to the lowest quantiles of the distribution of a set of financial variables (including, stock returns) and, hence, to systemic risk scenarios. However, traditional methods based on quantiles do not allow the researcher to identify the source of the shocks to the system; rather, they calculate the marginal contribution of each company to the risk of the system as a whole.

Our contribution to the literature is the examination of the characteristics and stability of systemic risk and uncertainty, in relation to the dynamics of the banking sector stock returns. Particularly, we are interested in exploring relevant hypotheses for the economics discipline regarding the stability of the systemic risk propagation mechanism across the global banking sector, and about the importance of equity market uncertainty as a source of systemic risk for global financial institutions. Both issues are instrumental for the design of macro policies, seeking to reduce systemic risk materialization episodes, or to construct a more resilient global banking sector in the forthcoming decades. Hence, we aim to measure the systemic risk in the global banking sector that arises from two primary sources: an unobservable systemic risk factor by White et al. (2015) and an economic equity market uncertainty factor (EMU) provided by Baker et al (2016). Our proposal is novel in three respects. First, we consider the evolving nature of systemic risk, a characteristic mainly overlooked in the literature despite having evident policy and practical implications for the banking industry.[26] We provide evidence regarding the stability of the relationship between systemic shocks and the banks' responses over the last decade. This sort of evidence is new to the literature and is supportive of past claims, made in the field of macroeconomics (Stock and Watson, 2012), which hold that during the global financial crisis the financial system may have faced stronger versions of traditional shocks rather than a new type of shock.

Second, we undertake an empirical study of the role of equity market uncertainty, as measured by Baker et al. (2016), as a systemic risk factor for the banking industry. Uncertainty is known to play a critical role in determining economic dynamics during episodes of crisis and, in recent years, its study has

[24] See Bisias et al. (2012) for a review.

[25] These methods were originally proposed by Acharya et al. (2017) and Adrian and Brunnermeier (2014). Numerous empirical implementations followed, for example, in the work of Anginer et al. (2014a, 2014b), Bernal et al. (2014), or Drakos and Kouretas (2015).

[26] Two exceptions to this point are the studies by Straetmans and Chaudry (2015) and Kolari and Sanz (2017), which we discuss in the next section.

attracted much attention in the literature to account for the nonlinear negative dynamics that arise during episodes of economic distress (Bloom, 2009; Jurado et al., 2015). Empirical tools are now available that can provide accurate measurements of uncertainty (Baker et al. 2016), and its inclusion as an unobservable factor enhances our understanding of banking sector behavior during episodes of systemic stress in the financial markets. We report that for most of the banks analyzed, especially over the last decade, uncertainty is indeed a relevant consideration. As expected, more uncertainty leads to a reduction in equity prices in the banking industry, and this behavior has become more pronounced in the last few years, especially when compared to the situation 15 years ago.

Finally, we emphasize the vulnerability of each institution to systemic shocks (either EMU or systemic risk factors), rather than the vulnerability of the system as a whole to the failure of one specific, perhaps important, financial institution. The perspective we adopt has received considerably less attention in the literature[27]. By implementing our model, we are able to rank banks in accordance with their vulnerability to two common shocks: an unobservable systemic risk factor and the equity market uncertainty shock. Thus, we seek to identify systemically vulnerable financial institutions under scenarios of financial distress. Notice that the two factors in our model were selected as to measure two main different sources of vulnerability in the global banking sector. While the systemic risk indicator may be interpreted as a "financial" risk shock, the EMU index quantifies "economic" uncertainty related with equity markets. This theoretical separation allows us to interpret our main findings as arising from the financial and macroeconomic (real) sides of the economic system. This distinction and the importance of its inclusion in the empirical exercise that we conduct in what follows are crucial to achieving a deeper understanding of the way in which the propagation of shocks occurs within and between financial and real markets.[28].

Our model involves combining dynamic factor models with quantile regressions, in line with Ando and Tsay (2011) and White et al. (2015).[29] Yet, unlike Ando and Tsay (2011), who are not concerned with systemic risk but rather with forecasting asset returns, we construct the factors for inclusion in the factor-augmented quantile regression by differentiating between a traditional systemic risk factor and an equity market uncertainty factor. Similar

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[27] Some noticeable recent examples given by Hartmann et al. (2006), Jonghe (2010) and Straetmans and Chaudhry (2015).

[28] See for example the theoretical by Brunnermeier and Sannikov (2014) to motivate the importance of considering the interplay between macro and financial markets.

[29] Factor models are popular in the asset pricing literature (Fama and French, 1993; Cochrane, 2005), while quantile regressions have gained considerable impetus in the financial branch in recent years (Engle and Manganelli, 2004; Li and Miu, 2010; Ciner et al. 2013; Mensi et al., 2014; among others).

to White et al. (2015), we consider the systemic factor as being contemporaneously exogenous from the point of view of each bank. In contrast with them, we do not construct (pseudo) quantile impulse response functions, and this allows us to expand the analysis by including more relevant factors (e.g., the uncertainty factor). That is, our model lacks dynamics, and therefore it may exist additional feedback beyond the first period going from the idiosyncratic bank dynamics to the system dynamics. This can conduce to a total impact of the systemic shock higher than the one observed in the first period, which we report here. Nevertheless, we restrict our attention to the effect observed when the systemic shock first arises, which is the most relevant point in the total dynamic impact[30]. This contemporaneous reaction is crucial in terms of systemic risk and we aim at examining its stability through time. To this end we test for the stability of the quantile coefficients in an endogenous fashion, following the proposals made by Oka and Qu (2011). This last step allows us to determine whether there were changes in the propagation of systemic risk in the global banking industry during and after the crisis. The outcome we report is, in general, negative in this regard.

In sum, we measure, by the first time, the role of equity market uncertainty as a systemic risk factor for the global banking sector. We test whether the relationship between economic uncertainty and banks' returns, and a previously identified systemic risk factor and banks' returns is stable during the sample period, which includes the global financial crisis, in an endogenous fashion, which is also new for the literature. We employed a methodology that allows us to focus on a specific quantile of interest**,** conditional on the systemic risk factors that we identified. This is also new, given that in the systemic risk exercises that have used quantiles so far, systemic risk factors are omitted and the estimates refer to unconditional quantiles of the dynamic distribution of returns (or to estimates conditional on certain observation as opposed to quantiles). Finally, we also provide a ranking of systemically vulnerable financial institutions that focuses on the vulnerability of each institution to the systemic risk factors, as opposed to the extant literature that has mainly focused on the effect of each institution on the rest of the system.

The rest of this paper is organized as follows. In the next section we undertake a general review of the literature examining systemic risk, so as to place our study in a broader context and to illustrate just where our contribution fits in the field. The third section provides a detailed explanation of our methodology. In the fourth section we present our main results and, finally, in the fifth section we conclude and discuss the limitations of this study and identify future lines of research.

[30] See for example Figures 2 to 4 in White et al. (2015) in which the first effect is always the maximum of the pseudo impulse responses.

4.2. Related literature

Systemic risk is traditionally considered as comprising various phenomena that represent substantial costs to the real economy and which, as such, have attracted significant research efforts. Allen and Carletti (2013) summarize these phenomena as panics (associated with banking crises due to multiple equilibria); banking crises due to asset price falls; contagion; and, foreign exchange mismatches in the banking system. The authors stress the historical importance of panics in accounting for systemic risk. Panics, they argue, are self-fulfilling events that arise because agents have uncertain consumption patterns and, consequently, uncertain investment plans, which are costly to implement. In a scenario in which depositors believe that other depositors will withdraw their funds prematurely, then all agents find it optimal to redeem their claims, sending the market into panic (see the seminal works by Bryant, 1980, and Diamond and Dybvig, 1983).

In the case of banking crises, Allen and Carletti (2013) identify several possible reasons as to why the prices of assets held by banks might drop, generating the appearance of systemic risk in the real economy. They include, but are not limited to, the business cycle dynamics, the bursting of real estate bubbles, mispricing due to inefficient liquidity provision and limits to arbitrage, sovereign defaults and interest rate increases. In each of these cases, whether they are related to natural economic dynamics (for instance the real cycles of the economy, as reviewed by Allen et al., 2009) or to behavioral biases in agent decision-making (Allen and Gale, 2007), when asset prices fall, this might result in significant solvency problems for banks and, hence, in systemic risk.

Contagion is another important source of systemic risk that seems to have been particularly relevant in the most recent global financial crisis. This phenomenon refers to the possibility that the distress of one financial institution propagates to others in the system and, thus, leads to a systemic crisis (Allen et al., 2009, provide a survey of this literature). Finally, Allen and Moessner (2010) describe currency mismatches in the banking system, created by banks lending in a low interest rate foreign currency, and then funding these loans in domestic currency. When exchange rate reversals are made, as occurred during the Asian crisis in 1997, the solvency and liquidity of the whole banking system may be compromised.

More recently, systemic risk has received considerable attention from both academics and regulators, since it is thought to lie at the core of the 2007-2009 crisis and to be a key factor in understanding crisis propagation to the real economy. In the main, research has explored data series from the US and the Eurozone and has analyzed systemic risk from a range of perspectives.

One strand of this literature has analyzed the systemic risk arising from individual financial institution spillovers, i.e., it has focused on measuring the impact that individual shocks attributable to specific institutions may have on the system as a whole. For example, Avramidis and Pasiouras (2015), using factor models and multivariate extreme dependency statistics, study spillovers between individual financial institutions. They highlight the significant underestimation of the capital requirements of financial institutions if extreme event dependence is ignored when estimating solvency ratios. Kanno (2015) and Cont and Minca (2016) undertake network analyses to explore interbank bilateral exposures and over-the-counter credit default swaps, respectively, and report large spillovers during the global financial crisis. In the same line of research, Bongini et al. (2015) and Castro and Ferrari (2014) analyze systemically important financial institutions (SIFIs) and their market effects. While the former apply event study methodology to determine the impact of inclusion as a SIFI on market prices, the latter explore the use of CoVaR (Conditional Value at Risk) as a measure of an institution's systemic importance.[31]

Alternative measures, including V-Lab stress tests, designed to account for 'the risk that risk itself may change', have been compared with the stress test indicators used by the Supervisory Capital Assessment Program in the US and by the European Banking Authority (which replaced the Committee of European Banking Supervisors) in the EU (see Acharya et al., 2012; Acharya et al., 2014). In the same vein, nonlinear models using flexible parameterizations, such as those allowed by vine copulas, have been analyzed for example in Brechmann et al. (2013), with empirical applications to both the insurance and banking sectors. Finally, Singh et al. (2015) analyze the risk behavior of the banking sector at the individual level and then scale these outcomes at the EMU-country level, using distance-to-default models and vector autoregression estimates.

Another strand of the literature has analyzed the systemic risk arising from extreme market scenarios in an aggregate fashion. In other words, it has explored the sensitivity of financial institutions to 'systemic factors', which can be treated as observable or unobservable. The former are related, for example, to liquidity considerations, as studied by Pierret (2015) and Jobst (2014b). While the first of these authors constructs a model that blends questions of liquidity and solvency, the second proposes adjusting traditional systemic risk indicators using liquidity constraints. Other observable factors include disruptions in economic conditions, as studied for example by Calmès and Théoret (2014), and such factors as interbank exposures, asset prices, and sovereign credit risks (Paltalidis et al., 2015).

In contrast, a number of studies have preferred to focus on unobservable

[31] CoVaR was originally proposed by Adrian and Brunnermeier (2014) for the estimation of increments in a firm's marginal expected shortfall, under a scenario of financial turmoil. It has been extended to the bivariate setting, for example, by Lopéz-Espinosa et al., 2015.

factors. For example, Kim and Kim (2014) estimate a 'systemic bubble index' to determine the investment dynamics of stock investors for financial institutions, and which should serve as an early warning signal of systemic fragility. Alter and Beyer (2014) quantify spillovers between sovereign credit markets and banks in the euro area, but they treat the factors as exogenous-unobservable forces affecting the dynamics of CDSs.

Finally, a new branch of the systemic risk literature has started to explore the evolving nature of systemic risk. This branch (implicitly or explicitly) considers systemic risk as a policy regime-dependent problem. As such, it seeks to take into account changes in terms of the regulatory framework (i.e., Basel III, the Dodd-Frank reform), macro-prudential regulation, and individual risk preferences. Claessens et al. (2013) investigate the efficacy of macro-prudential policy for preventing systemic risk and report that such measures have helped mitigate bank leverage and exposure to the volatility of financial assets. However, others, such as Calluzzo and Dong (2015), question whether the reduction in risk faced by individual institutions correlates with a decrease in systemic risk. They conclude that it does not, and indeed, using a quasi-experimental design, they document an increment in the amount of contagion in the post-crisis financial system, and hence in the vulnerability of the financial market to systemic risk.

Similarly, Straetmans and Chaudhry (2015) evaluate multiple market-based measures for US and eurozone individual bank tail risk and bank systemic risk, and report results that suggest that both are higher in the US than in the eurozone regardless of the sample period (pre- and post-crisis). They also find that the magnitude of the two risk types increased in both samples, taking the crisis as a threshold. This contribution can be seen as the closest to ours. The authors analyze systemic spillovers using extreme value theory and they aim to test for the stability of the results. They do both an analysis of the whole system sensitiveness to each financial institution, and of each bank to aggregate systemic factors (such as stock market indices, sectorial world-wide and regional indices and housing prices). Nevertheless, their systemic factors are different to ours and their estimates correspond to co-crash probabilities of banks, conditioning on sharp drops on the non-diversifiable factors. To do the latter they need to focus on particular dates at witch the systemic risk indicators drop in a significant magnitude. By the contrary, we use our full sample to estimate the conditional quantiles of the banks' return distributions. These quantiles are by construction conditional on our systemic factors and in this way we manage to use the information more efficiently. More importantly, we test for the stability of the estimates describing the propagation mechanism, but different from Straetmans and Chaudhry (2015) who impose *ad hoc* the possible structural change of the series, we do so in an endogenous fashion, following the proposal by Oka and Qu (2011). The latter approach has several advantages, which have been extensively documented in the literature of structural changes in time series analysis (see Perron (2006) for a survey). Basically, imposing the break dates might derive in spurious detection of changes in the data generating process. Therefore the search should be ideally carried up in an endogenous fashion.

The selection of our systemic factors and our quantile regression methodology, unable us to obtain stable model coefficients, before and after the global financial crisis. This means that our factors suffice to explain the quantile variations before and after the crisis, while Straetmans and Chaudry (2015) estimates experience a great amount of variation (with marked jumps of the "tail-betas" that they calculate). This is an advantage, because our model does not become invalid once the systemic risk factors achieve a certain threshold.

The present study is related to all three branches of the literature outlined above, but primarily with the last two. It is closely associated with the second group of studies because we are concerned with the sensitivity of individual institutions to factors of systemic risk. In line with Kim and Kim (2014) and White et al. (2015), we treat these factors as unobservable in nature and, in line with Calmès and Théoret (2014), Alter and Beyer (2014), and Paltalidis et al. (2015), we treat them as exogenous from the point of view of each financial institution. It is also closely associated with the third group because it focuses on the dynamics of systemic risk. We explicitly test for the stability of the parameters in our factor quantile model, seeking to identify any possible structural changes in the shape of risk transmission during the sample period, in an endogenous fashion. Finally, in relation to the first set of papers, our study can be considered as providing a tool to account for the 'risk that risk itself may change', in line with the V-Lab stress test (although using different methodologies).

Kolari and Sanz (2017) utilize neural network mapping technology to assess the dynamic nature of systemic risk over time in the banking industry. They report informal graphical evidence suggesting that systemic risk peaked in 2009 and remained thereafter. Their strategy consists of a visual inspection of the changes in the network's maps of the 16 main commercial banks in the US during the crisis period. The changes reported by the authors are gradual, so they are not related to dramatic changes or structural breaks from one year to another. Different to these authors we focus here in permanent changes of the systemic risk propagation mechanisms following the global financial crisis and we provide statistical tests of such changes. We also analyze a longer period of time and a considerable greater number of banks.

Notice that different to ours, other measures of systemic risk, based on quantiles, such as the marginal expected shortfall (MES) of Acharya et al. (2017) estimate the stock return reaction of bank i to bad market outcomes. They are intended to provide a measure of the resilience of each individual institution to systemic distress scenarios. In this way, they aim to estimate the marginal contribution of each bank to systemic financial distress: The more negative the outcome of a particular bank is, the more this institution will contribute to destabilize the system during periods of generalized distress. You can notice that the emphasis of the exercise using MES is precisely on *how much the system will be affected by the idiosyncratic bank performance* during bad market times. On the contrary, our definition of SVFIs emphasizes on *how the system impacts on the bank i, at any time*, which is a complementary approach. For this reason, we do not restrict our attention to bad market outcomes, but to bad individual stock realizations of the financial institutions (i.e. to the lowest quantiles of the banks' return distribution).

4.3. Methodology

As discussed, our methodological proposal involves combining dynamic factor models with quantile regression. Thus, we construct the factors to be included in the factor-augmented quantile regression, differentiating between a traditional, systemic risk factor affecting the global financial sector and an equity market uncertainty factor. We conduct the estimation in a three-step approach: first, we construct the systemic factor; second, we use this and the EMU factor provided by Baker et al. (2016) as explanatory variables in a traditional quantile regression; and, third, we test the stability of the parameters, seeking to identify changes in factor load coefficients that might be attributable to the crisis.

Following Bai and Ng (2008), let N be the number of cross-sectional units, that is, the number of banks in our sample, and let T be the number of time series observations. For $i = 1 \dots N$ and $t = 1 \dots T$, our factor model can be defined as:

$$x_{it} = \lambda_{1,i} f_{1,t} + \lambda_{2,i} f_{2,t} + e_{it} \quad , \tag{4.1}$$

or more compactly as $\boldsymbol{x}_t = \boldsymbol{\alpha} \boldsymbol{f}_t + \boldsymbol{e}_t$ with $\boldsymbol{x}_t = (x_{1t}, \dots, x_{Nt})'$, $\boldsymbol{f}_t = (f_{1t}, f_{2t})'$, $\boldsymbol{e}_t = (e_{1t}, \dots, e_{Nt})'$. $\boldsymbol{x}_t$ is a *N*-dimensional observable random vector of stock returns of the banks in our sample, $\boldsymbol{f}_t$ is a *2*-dimensional vector of latent factors.

$f_{1,t}$ is an unobservable systemic risk factor that impacts the *N* financial institutions in our sample via coefficients $\lambda_{1,i}$. Thus, it can be estimated using the first principal component of the $(N \times T)$ matrix of financial institutions' stock returns in the cross-sectional dimension. This procedure enables us to treat the consistently estimated factors as non-generated regressors in subsequent stages of our procedure (Bai and Ng, 2002; Stock and Watson, 2002), which is important for inference.[32]

$f_{2,t}$ is a general equity market uncertainty factor that may potentially impact the banks via $\lambda_{2,i}$. This uncertainty factor is, in principle, unobservable, as well. However, recent advances in the discipline mean we can construct indices of economic uncertainty that impact the equity market. Specifically, here, we use the equity market uncertainty factor proposed by Baker et al. (2016). These authors construct their measure of uncertainty by searching each paper in the NewsBank database looking for terms related to economic and policy uncertainty.[33] This direct measure of equity market uncertainty allows us to trace the dynamic of this unobservable and systemic factor.

The first unobservable factor was previously identified in the literature by White et al. (2015), as we already emphasized. Moreover, it is naturally related to a market factor, because it summarizes the common variation in all the series of stock returns in the financial sector in a CAPM' style, and therefore, it should be the starting point of any factor analysis about systemic risk (or asset pricing).

The inclusion of EMU requires a more detailed explanation. We need a factor that helps to identify recessionary states in the market, and that provides new information additional to the market factor. We ideally require a variable with predictive power on the state of the economy and at the same time with a theoretical justification to support its inclusion. Indeed, this is the case of very few factors in the literature and uncertainty is one of them. Balcilar et al. (2016) and Segnon et al. (2016) provide evidence of the predictive power of uncertainty in the GDP forecast and Balcilar and Gupta (2016) provide evidence of the prediction power of uncertainty in inflation. On the other side, Bansal and Yaron (2004), Bloom et al. (2007), Bloom (2009), Jurado et al. (2015) and Chuliá et al. (2017), to name just a few, have extensively

[32] We construct the systemic risk measure in line with White et al. (2015). Unlike us, they estimated the principal components of each financial sector (banks, insurers and others) and then aggregated the factors using the market capitalization of each sector as weights. We also tried estimating the factors that affect each sector separately, and included all three in the estimations, but the amount of multicollinearity among the three factors, indicated that they were likely to be measuring the same unobservable shocks. For this reason, we preferred to include only one general factor as we explain in the main text.

[33] Specifically, they search for articles containing the words 'uncertainty' or 'uncertain'; 'economic' or 'economy'; and, one or more of the following terms: 'equity market', 'equity price', 'stock market', or 'stock price'. Thus, to satisfy their criteria for inclusion, the article must include a term from each of the three categories (that is, uncertainty, the economy, and the stock market). Further details about the construction of the index can be found at www.policyuncertainty.com and in Baker et al. (2016).

documented, and modeled, how uncertainty may affect price formation in the market, or how it may shape the dynamics of the economic activity as a whole.

Finally, one could argue that while the market factor is more related to expected variations within the financial system, equity market uncertainty is more related to unexpected movements in the time series returns, related to the economic system. Therefore they are complementary and hence natural candidates to construct our factor model (see for example Chuliá et al. (2017) for an extensive discussion of the differences between expected and unexpected shocks).

Here we keep the focus on the systemic risk interpretations accompanying our factors, but we acknowledge that this exercise is much related to those performed within the asset pricing literature aiming to explain the equity premium, and therefore, other factors such as size, book to market ratios, momentum, etc. might be explored in future exercises. Nevertheless, the theoretical constructs that underlie uncertainty are very appealing and for this reason we consider that it remains an attractive starting point for systemic risk analysis.

The model in Eq. 1 relates the 'average' scenarios for the bank stock returns distribution to the systemic factors. However, our definition of systemic risk means we need to focus on the shocks that occur during extreme negative scenarios. To this end we expand regression (4.1) as:

$$q_i^\tau(x_{it}|\boldsymbol{f_t};\boldsymbol{\alpha}) = \boldsymbol{\alpha}(\tau)'\boldsymbol{f_t}, \qquad (4.2)$$

where $\alpha(\tau)$ is a vector of coefficients that depends on the quantile τ, q_i^τ. Unlike classical factor theory, which focuses on the factor's mean impact on the endogenous variables, quantile estimates allow us to explore different portions of the conditional distribution of the stock returns. Quantile regressions are known to be robust to outliers and this is particularly important when analyzing financial time series. They are also semi-parametric in nature and, therefore, we require minimal distributional assumptions on the underlying data generating process. Moreover, quantile regressions offer greater flexibility in the analysis of different market scenarios. For instance, lower quantiles can be interpreted as extreme negative situations, corresponding for example to setting $\tau = 0.1$, and therefore the estimations are directly related to systemic risk scenarios. Quantile regressions have been incorporated in the factor pricing literature, for instance in Gowlland et al. (2009), Ando and Tsay (2011), Allen et al. (2013) and Autchariyapanitkul et al. (2015), but they remain underexplored in the systemic risk framework.

Moreover, using the matrix $\widehat{\boldsymbol{\alpha}}(\tau)$, the banks can be sorted according to their sensitivity to each of the underlying factors. The ordering is bi-dimensional in nature, and so the companies with greatest exposure to the two factors can be identified as systemically vulnerable financial institutions (SVFIs), which we propose as a complementary concept to Global-SIFIs. This ranking provides valuable information from the point of view of the banks that participate in the market, since it provides the basis for capital adjustments that take into account the idiosyncratic vulnerabilities of each institution.

Finally, we use recent advances in the econometrics literature to test the stability of the load coefficients in the matrix $\widehat{\boldsymbol{\alpha}}(\tau)$. These include a test for multiple endogenous structural breaks in single quantile regression coefficients, as explored in Oka and Qu (2011). By so doing, we are able to determine whether the financial crisis has significantly shaped the systemic risk dynamics in the banking industry. The procedure devised by Oka and Qu (2011) involves constructing a break estimator that is the global minimizer of the check function over all permissible break dates. The underlying assumptions are mild, and they restrict only a neighborhood surrounding the quantiles of interest, which makes it a suitable tool for our purposes.

In what follows, we briefly review their proposal, but we invite the interested reader to consult the full article by Oka and Qu (2011) for further methodological details about derivations and their main underlying assumptions.

For the purposes of estimation, we assume the conditional quantile function in Eq. 2 to be linear in parameters and to be affected by m structural changes, as follows:

$$q_i^\tau(x_{it}|\boldsymbol{f_t};\boldsymbol{\alpha}) = \begin{cases} \boldsymbol{\alpha}_1(\tau)'\boldsymbol{f}_t, & t = 1, \dots, T_1^0 \\ \boldsymbol{\alpha}_2(\tau)'\boldsymbol{f}_t, & t = T_1^0 + 1, \dots, T_2^0 \\ & \vdots \\ \boldsymbol{\alpha}_{m+1}(\tau)'\boldsymbol{f}_t, & t = T_m^0 + 1, \dots, T \end{cases}, \tag{4.3}$$

where τ denotes the quantile of interest, and where, as stated before, $\boldsymbol{\alpha}_j(\tau)$ $(j = 1, \dots, m + 1)$ are the unknown parameters that are quantile dependent, and T_j^0 $(j = 1, \dots, m)$ $(j = 1, \dots, m)$ are the unknown break dates. In the absence of structural change, the model in Eq. 3 can be estimated by solving:

$$\min_{\boldsymbol{\alpha} \in \mathbb{R}^N} \sum_{t=1}^{T} \rho_\tau(x_{it} - \boldsymbol{\alpha}'\boldsymbol{f_t}), \tag{4.4}$$

where $\mathbb{R}^N$ are N-dimensional Real, for each cross-sectional unit in the factor model, but we eliminate the sub-index in $i = 1, \dots, N$ to avoid unnecessary notation. $\rho_\tau(u)$ is the check function given $\rho_\tau(u) = u\big(\tau - 1(u < 0)\big)$ (see Oka and Qu, 2011, and Koenker, 2005, for further details). Now suppose that the τth quantile (in our case a low quantile, such as the 10th percentile) is affected by m structural changes, occurring at unknown dates $(T_1^0, \dots, T_m^0)$. Then, we can define the following function for a set of feasible break dates $T^b = (T_1, \dots, T_m)$:

$$S_T(\tau, \boldsymbol{\alpha}(\tau), T^b) = \sum_{j=0}^{m} \sum_{t=T_j+1}^{T_{j+1}} \rho_\tau\left(x_{it} - \boldsymbol{\alpha}'_{j+1}(\tau)\boldsymbol{f_t}\right), \quad (4.5)$$

where $\boldsymbol{\alpha}(\tau) = \left(\boldsymbol{\alpha}_1(\tau), \dots, \boldsymbol{\alpha}_{m+1}(\tau)\right)$, $T_0 = 0$ and $T_{m+1} = T$. Following Bai (1995, 1998), Oka and Qu (2011) propose estimating the break dates and coefficients $\boldsymbol{\alpha}(\tau)$ jointly by solving the following minimization problem:

$$\left(\widehat{\boldsymbol{\alpha}}(\tau), \hat{T}^b\right) = \mathrm{argmin}_{\boldsymbol{\alpha}(\tau), T^b \in \mathbb{T}} S_T(\tau, \boldsymbol{\alpha}(\tau), T^b), \quad (4.6)$$

where $\widehat{\boldsymbol{\alpha}}(\tau) = \left(\widehat{\boldsymbol{\alpha}}_1(\tau), \dots, \widehat{\boldsymbol{\alpha}}_{m+1}(\tau)\right)$ and $\hat{T}^b = \left(\hat{T}_1, \dots, \hat{T}_m\right)$. Specifically, for a given partition of the sample, the coefficients are estimated by minimizing $S_T(\tau, \boldsymbol{\alpha}(\tau), T^b)$. Then a search has to be conducted over all permissible partitions to find the break dates that achieve the global minimum. In Eq. 4.6, $\mathbb{T}$ denotes this set of possible partitions and ensures that each estimated regime is a positive fraction of the sample. This is what we referred to above when discussing the feasible break date.

In our empirical application, we permit a maximum number of regimes $m = 3$, corresponding to two structural changes, so as to limit computational costs. This means our break dates should be interpreted as the "biggest" structural changes in the sample. Nevertheless, we used the SQ_τ statistic proposed by Qu (2008) to determine the optimal number of breaks in case it was less than three. The SQ_τ test is designed to detect structural changes in a given quantile τ, and is defined as:

$$SQ_\tau = \sup_{\lambda \in [0,1]} \left\| \left(\tau(1-\tau)\right)^{-1/2} \left[H_{\lambda,T}\left(\widehat{\boldsymbol{\alpha}}(\tau)\right) - \lambda H_{1,T}\left(\widehat{\boldsymbol{\alpha}}(\tau)\right)\right] \right\|_\infty, \quad (4.7)$$

where,

$$H_{\lambda,T}\left(\widehat{\boldsymbol{\alpha}}(\tau)\right) = \left(\sum_{t=1}^{T} \boldsymbol{f_t} \boldsymbol{f'_t}\right)^{-1/2} \sum_{t=1}^{\lfloor \lambda T \rfloor} \boldsymbol{f_t}\, \psi_\tau(x_{it} - \widehat{\boldsymbol{\alpha}}'(\tau)\boldsymbol{f_t}), \quad (4.8)$$

$\widehat{\boldsymbol{\alpha}}'(\tau)$ is the estimate using the whole sample and assuming no structural change. $\|\cdot\|_\infty$ is the sup norm. We also require the test labeled $SQ_\tau(l+1|l)$ in case we detect more than one break. This test is employed as follows: suppose a model with l breaks has been estimated with the estimates denoted by $\hat{T}_1, \dots, \hat{T}_l$. We proceed by testing each of the $l+1$ segments for the presence of an additional break. We let $SQ_{\tau,j}$ denote the SQ_τ test applied to the jth segment as follows:

$$SQ_{\tau,j} = \sup_{\lambda \in [0,1]} \left\| \left(\tau(1-\tau)\right)^{-1/2} \left[H_{\lambda,\hat{T}_{j-1},\hat{T}_j}\left(\widehat{\boldsymbol{\alpha}}_j(\tau)\right) - \lambda H_{1,,\hat{T}_{j-1},\hat{T}_j}\left(\widehat{\boldsymbol{\alpha}}_j(\tau)\right)\right] \right\|_\infty, \quad (4.9)$$

and analogous definitions for $H_{\lambda,\hat{T}_{j-1},\hat{T}_j}$ and $H_{1,,\hat{T}_{j-1},\hat{T}_j}$ to those presented in Eq. 8. In this case $SQ_\tau(l+1|l)$ is equal to the maximum of the $SQ_{\tau,j}$ over $l+1$ segments:

$$SQ_\tau(l+1|l) = \max_{1 \le j \le l+1} SQ_{\tau,j}. \quad (4.10)$$

We reject this in favor of a model with $l+1$ breaks if the resulting value is sufficiently large and provided $l<2$, so as to keep the computational costs to a minimum. The critical values for performing these comparisons are provided by Oka and Qu (2011), while their construction is in line with the logic underpinning the work by Bai and Perron (1998).

4.4. Data

To construct the systemic risk factor affecting the financial institutions in our sample we used 113 banks, 59 insurance companies (life, non-life and reinsurance), and 50 firms providing other financial services (i.e., asset management, specialty finance, financial administration, and investment services). All 222 financial institutions are listed in Table 4.1 (banks) and Table A in the appendix. Our sample resembles that employed by White et al. (2015). Those authors used in their estimations firms belonging to three main global sub-indices: banks, financial services and insurance, according to the firms' market capitalization. We do so seeking for some comparability between our results, in terms of the stability of the quantile coefficients, and the main findings of White et al. (2015). Their data set include the biggest institutions in terms of market capitalization in each region and therefore we expect them to be the most relevant ones in terms of global financial stability. We eliminated from our original sample companies with a large number of missing observations at the beginning or the end of the sample period. All data were taken from Datastream. The sample includes weekly closing prices, for each Friday, from 21 July 2000 to 20 November 2015. Prices were transformed into continuously compounded log- returns, giving an estimation sample size of 800 weeks in total.

The equity market uncertainty index was retrieved from the webpage www.policyuncertainty.com. We aggregated this daily index over the week to obtain a weekly index. In this way, we avoided excluding any uncertainty episodes that occur on days of the week other than Friday. We transformed the original index to natural logarithms and performed two unit root tests (the augmented Dickey-Fuller test and the Dickey-Fuller generalized least squares test) on the series. In both cases, we rejected the null of a unit root with statistics equal to -4.52 and -6.48, respectively, and associated critical values at the 1% significance level: 2.58 and -2.57. This means that the equity market uncertainty index can be included without differentiating it in the quantile regressions that we present in what follows. This eases the explanation of the results, as the estimated effects will be directly attributable to the impact of log-uncertainty variations on the banks' returns.

Table 4. 1. Banks in our Sample

NAME	MNE	NAME	MNEM	NAME	MNEM	NAME	MNEM
77 BANK	SSBK	COMMERZBANK (XET)	CBKX	HUNTINGTON BCSH.	HBAN	PEOPLES UNITED FINANCIAL	PBCT
ALLIED IRISH BANKS	ALBK	CREDIT SUISSE GROUP N	CSGN	HYAKUGO BANK	OBAN	ROYAL BANK OF SCTL.GP.	RBS
ALPHA BANK	PIST	BCA.PICCOLO CDT.VALTELL	CVAL	HYAKUJUSHI BANK	OFBK	REGIONS FINL.NEW	RF
AUS.AND NZ.BANKING GP.	ANZX	CANADIAN IMP.BK.COM.	CM	IYO BANK	ISP	RESONA HOLDINGS	DBHI
AWA BANK	AWAT	CHIBA BANK	CHBK	INTESA SANPAOLO	IYOT	ROYAL BANK OF CANADA	RY
BANK OF IRELAND	BKIR	CHUGOKU BANK	CHUT	JP MORGAN CHASE & CO.	ISP	SEB 'A'	SEA
BANKINTER 'R'	BKT	SUMITOMO MITSUI TST.HDG.	SMTH	JYSKE BANK	JYS	STANDARD CHARTERED	STAN
BARCLAYS	BARC	CITIGROUP	C	JOYO BANK	JOYO	SVENSKA HANDBKN.'A '	SVK
BB&T	BBT	COMERICA	CMA	JUROKU BANK	JURT	SWEDBANK 'A'	SWED
BANCA CARIGE	CRG	COMMONWEALTH BK.OF AUS.	CBAX	KBC GROUP	KB	SYDBANK	SYD
BANCA MONTE DEI PASCHI	BMPS	DANSKE BANK	DAB	KAGOSHIMA BANK	KABK	SAN-IN GODO BANK	SIGB
BANCA POPOLARE DI MILANO	PMI	DBS GROUP HOLDINGS	DBSS	KEIYO BANK	CSOG	SHIGA BANK	SHIG
BANCA PPO.DI SONDRIO	BPSO	DEUTSCHE BANK (XET)	DBKX	KEYCORP	KEY	SHINKIN CENTRAL BANK PF.	SKCB
BANCA PPO.EMILIA ROMAGNA	BPE	DEXIA	DEX	LLOYDS BANKING GROUP	LLOY	SUMITOMO MITSUI FINL.GP.	SMFI
BBV.ARGENTARIA	BBVA	DNB NOR (FRA)	DNB	M&T BANK	MTB	SUNTRUST BANKS	STI
BANCO COMR.PORTUGUES 'R'	BCP	DAISHI BANK	DANK	MEDIOBANCA (FRA)	MB	SURUGA BANK	SURB
BANCO ESPIRITO SANTO SUSP	BES	EUROBANK ERGASIAS	EFG	NATIONAL BK.OF GREECE	ETE	TORONTO-DOMINION BANK	TD
BANCO POPOLARE	BP	ERSTE GROUP BANK	ERS	NATIXIS	KN@F	US BANCORP	USB
BANCO POPULAR ESPANOL	POP	FIFTH THIRD BANCORP	FITB	NORDEA BANK	NDA	UBS 'R'	UBSN
BANCO SANTANDER	SCH	FUKUOKA FINANCIAL GP.	FUKU	NANTO BANK	NANT	UNICREDIT	UCG
BNP PARIBAS	BNP	SOCIETE GENERALE	SGE	NATIONAL AUS.BANK	NABX	UNITED OVERSEAS BANK	UOBS
BANK OF AMERICA	BAC	GUNMA BANK	GMAB	NAT.BK.OF CANADA	NA	VALIANT 'R'	VATN
BANK OF EAST ASIA	BEAA	HSBC HOLDINGS	HSBC	NEW YORK COMMUNITY BANC.	NYCB	WELLS FARGO & CO	WFC
BANK OF KYOTO	KYTB	HACHIJUNI BANK	HABT	NISHI-NIPPON CITY BANK	NSHI	WESTPAC BANKING	WBCX
BANK OF MONTREAL	BMO	HANG SENG BANK	HSBA	OGAKI KYORITSU	OKBT	WING HANG BANK DEAD	WHBK

				BANK			
BK.OF NOVA SCOTIA	BNS	HIGO BANK DEAD	HIGO	OVERSEA-CHINESE BKG.	OCBC	YAMAGUCHI FINL.GP.	YMCB
BANK OF QLND.	BOQX	HIROSHIMA BANK	HRBK	BANK OF PIRAEUS	PEIR		
BANK OF YOKOHAMA	YOKO	HOKUHOKU FINL. GP.	HFIN	PNC FINL.SVS.GP.	PNC		
BENDIGO & ADELAIDE BANK	BENX	HUDSON CITY BANC.	HCBK	POHJOLA PANKKI A	POH		

Note: The other financial institutions included in our sample are listed in Table A in the appendix and adhere to the following sector classification: Asset Management, Specialty Finance, Investment Service, Consumer Finance, Financial Administration, Life Insurance, Property and Casualty Insurance, Full Line Insurance, Insurance Broker, and Reinsurance. Although we used all the institutions to estimate the systemic factor, we only employed the banks to estimate the systemic risk models. Data and classification were taken from Datastream.

4.5. Results and discussion

In this section we present our main results, including, the number of break dates in the empirical model for Eq. 2 for each of the 113 banks in our sample, and a summary of the coefficients associated with each regime, which relate equity market uncertainty and systemic risk factor to the banks' returns. We imposed a maximum number of breaks equal to 2, in the interests of reducing computational costs. As we already mentioned in the methodology, we permit a maximum number of structural breaks equal to 2. This means our break dates should be interpreted as the biggest structural changes in the sample. In principle, it would be possible to find more breaks (although not many of them, because only 40.71% of the sample presents at least two breaks), but in any case, such breaks would be smaller than the ones reported here. We emphasize that the reported break dates would not change if we allow for a greater number of breaks, because the estimation procedure is recursive: only after one statistically significant break has been detected, the algorithm searches for a new break point. Therefore our results are robust, by construction, to setting a higher upper bound for the number of breaks. This strategy would not change our conclusions and instead would complicate, not only the estimation, but also the presentation of our results.

A. The stable nature of systemic risk

Figure 4.1 shows our main results. For the 10th percentile we plotted each bank and its corresponding estimated break dates (the latter only when the null of no breaks is rejected and, therefore, at least one break is identified during the sample). A summary of the SQ statistics associated with these dates and the critical values are provided in Table 4.2. From these estimates, we find that 30 of the 113 banks (26.54% of the sample) did not present any structural breaks during the sample period; 37 (32.74%) presented only one statistically significant break; and 46 banks (40.71% of the sample) achieved the maximum number of breaks allowed (i.e., 2).

When structural breaks were present, they tended to concentrate on two dates: the first corresponded to weeks 27-28 (26 January 2001) and the second to week 55 (10 August 2001). The institution that houses a break date furthest from the sample origin was Deutsche Bank, with a break located at week 213 (20 August 2004). The estimations of the first break dates, however, might be biased, since our sample partition started in the 27th week, which means this first break date might be earlier. However, this does not change our main finding, namely, in none of the 10th percentile cases (corresponding to the worst scenarios in terms of market returns for the banking industry) were we able to detect a structural change in the model's parameters at a date close to that of the global financial crisis (2007-2009). Most of the banking returns that presented structural changes did so during a short interval, usually less than a year, corresponding roughly to 2001-2002 (though perhaps commencing a little earlier).

The period spanning 2000-2001 was associated with the dotcom crisis. This crisis had more pronounced effects in North America and its main financial partners than in other markets (and the break points tend to concentrate in a greater proportion in these markets). The period 2001-2004 was also related to a change in the monetary policy posture of the US' Fed and some regulatory changes in the main financial markets. The burst of the dotcom bubble had small effects on the real economy, which could have contributed to a change in the parameters relating the individual returns of some banks and the systemic factors, rather than to a change in the systemic factors themselves. Indeed, if the shocks witnessed by the markets during those years (2001-2004) had been more associated with the state of the economy, the model would have likely captured them, via the systemic factor that is calculated as the first principal component of the system. Indeed, the latter was probably the case during the global financial crisis in which there was not change in the parameters relating the factors and the banks. Nevertheless, as we emphasize in what follows, after analyzing the results in Table 4.3 we observe that, considering these breaks, the empirical distribution of the model's parameters seems remarkably stable, when we compare the beginning with the end of the sample. This stability prevents us from pursuing a more detailed explanation of these particular break dates at the beginning of the sample, or to overemphasize the statistical regimes that we found, even though they are practically equivalent in economic terms. In any case, our intuition points more to idiosyncratic factors explaining the breaks in 2000-2001 and 2004, than to a dramatic change in the market conditions or in terms of the way in which systemic risk propagates during the sample

Table 4.2. Summary Statistics of the Estimated ($SQ(\tau = 0.1)$ Statistics

	Number of Breaks	SQ1	SQ 2
25th percentile	0.00	1.496	1.45
50th percentile	1.00	1.871	1.70
75th percentile	2.00	2.345	2.27
Average	1.14	2.093	1.833
Critical value	-	1.624	1.521

Note: In the first column, we present summary statistics of the number of breaks detected (the maximum allowed being 2). In columns 2 and 3, we present the same information, plus the critical values for each SQ statistic at a 5% significance level. If the null is rejected, the associated break is statistically significant.

The results may appear somewhat surprising at first glance, given that they point to the relative stability of systemic risk transmission over the last decade – i.e., the coefficients describing the relationship between the common shocks affecting the financial institutions around the globe and the financial returns of those firms did not experience significant changes after (or during) the global financial crisis. Yet, our results are in line with previous findings in the macroeconomics literature. Stock and Watson (2012), seeking to elucidate the macroeconomic dynamics of the 2007-2009 Great Recession in the United States and the subsequent slow recovery, use a dynamic factor model with 200 variables. They draw two general conclusions: first, that the macroeconomic effects of many of the events that occurred during the 2007-2009 collapse were just larger versions of shocks previously experienced, and, as such, the economy responded in an historically predictable fashion; and second, that uncertainty and financial disruptions were two major forces behind the macro shocks that hit the economy during the crisis.

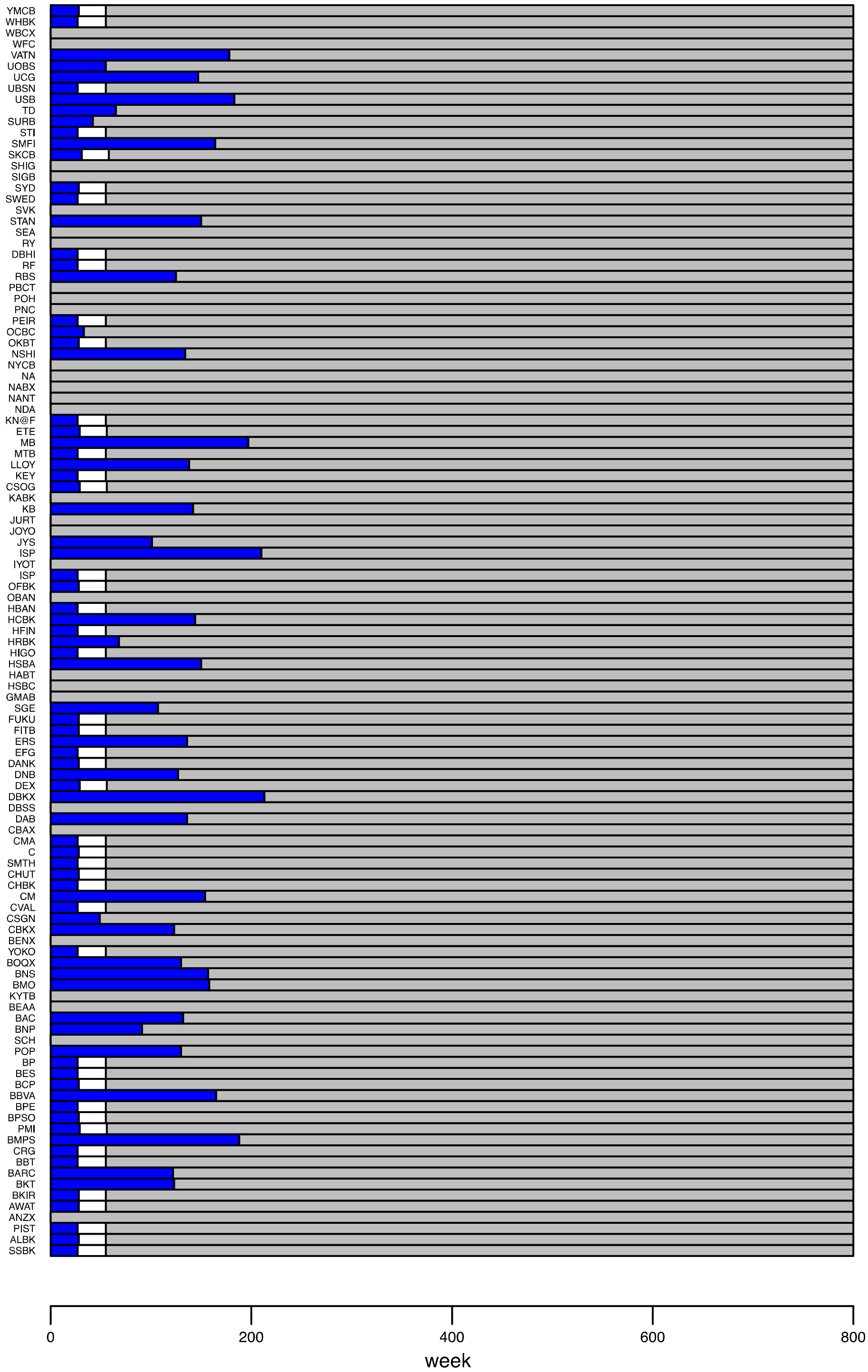


Figure 4.1. Structural Changes in Quantile Coefficients: Each horizontal bar represents a bank. The first regime in the sample is blue, the second regime is white and the third regime is grey. Only 30 banks display one regime, 37 two regimes and 46 three regimes (the maximum allowed). The regimes were identified endogenously, using a quantile regression with breaks. The model included two systemic factors: one common unobservable shock and equity market uncertainty.

These two main conclusions concern us here. First, we also found that the shocks to the financial industry during the crisis did not give rise to effects beyond those expected prior to the crisis. On the contrary, the banks' financial returns responded in a predictable way to the same shocks (uncertainty and the common shock). Stock and Watson's (2012) second conclusion also seems particularly relevant in this context. To understand why this is so, we first present (see Table 4.3) the summary statistics describing the set of coefficients for the "first" and "last" regimes in our sample. In other words, to make the estimations for the 113 banks comparable, we grouped the institutions' first and last regime coefficients, respectively. Note that the first regime for the 30 banks with no breaks is equal to the second and third regimes, given that there are no structural breaks in their models. For a further 37 banks (those with one break), these estimates correspond to the first and second regimes, and, finally, for the remaining 46 banks (those with two breaks), they correspond to the first and third regimes.

Table 4.3. First and Last Regime Summary Statistics of the Coefficients

	First regime			Last regime		
	α_0	α_1	α_2	α_0	α_1	α_2
Average	-0.27	0.13	-0.32	-0.37	0.15	-0.41
Std. Dev.	1.76	0.06	0.43	1.13	0.06	0.37
Median	-0.31	0.12	-0.25	-0.31	0.13	-0.37
75th perc.	0.40	0.17	-0.11	0.25	0.19	-0.20
25th perc.	0.39	0.17	-0.11	0.26	0.19	-0.20
Max	7.22	0.39	0.72	4.02	0.32	0.41
Min	-5.72	0.00	-2.44	-4.04	0.02	-2.18

Note: We present the summary statistics for the estimated coefficients for the first and last regimes in our sample: intercept, α1 (τ=0.1) and α2 (τ=0.1).

Note that in most instances the coefficients accompanying the uncertainty factor display a negative sign. Indeed in 84.07% of cases during the first regime, these coefficients are negative, and only in 15.93% are they positive and in no instances are they statistically significant. The same is true for the last regime, where only 8.77% of the coefficients are positive, but none are statistically significant.

In Table 4.4, we also report the percentage of coefficients that are statistically different from zero $\alpha_1(\tau = 0.1)$, at the 95% confidence level, which relate the returns of each bank and the common components of the system at the 10th percentile, and $\alpha_2(\tau = 0.1)$, which relates the returns and the market uncertainty factor, also at the 10th percentile. Table 4.4 also discriminates between the banks with no breaks, and banks with at least one break.

Table 4.4. Percentage of Statistically Significant Coefficients

	First regime		Last regime	
	α_1	α_2	α_1	α_2
Total	76.99%	35.40%	99.12%	56.64%
No breaks	100.00%	56.67%	100.00%	56.67%
At least one break	68.67%	27.71%	98.80%	56.63%

Note: We present the percentage of statistically significant coefficients at the 95% confidence level. We discriminated between banks with at least one break and banks with no breaks during the full period.

Several conclusions can be drawn from Tables 4.3 and 4.4. First, as expected, most of the time, α_1 is statistically significant at the 95% confidence level – that is, for 76.99% of the banks, the systemic shock (estimated as the first principal component of the system) matters during the first regime in the sample. The sign of the coefficient does not provide any information, because the factors are identified up to a column sign change when estimated using principal components (Bai and Ng, 2008). The number of significant relationships increases during the last regime when 99.12% of the institutions respond to this systemic factor in a statistically significant way.

Second, the uncertainty factor also seems relatively important as a systemic factor. During the first regime, 35.40% of the banks respond to this factor, and the proportion increases notably during the last regime, when 56.64% of the banks are affected by this equity market uncertainty factor in a statistically significant fashion. When we split the sample between those banks that faced no structural changes during the period analyzed, and those that faced at least one, we found that the equity market uncertainty factor was more important for banks with no breaks (56.67% of the times α_2 was significant at the 95% level) than it was for banks with breaks (27.71% in the first regime vs 56.63% in the last regime). Notice that the number of banks with a significant uncertainty-driven relationship may be even higher, because uncertainty and the unobservable component are likely to be correlated, and, moreover, for the first regime, the number of observation is considerably lower than for the second regime, which has well-documented effects on the estimated statistics for measuring significance.

All in all, equity market uncertainty is an important determinant of global banking system performance, and this importance seems to have increased after 2002. However, it remained equally important during and after the 2007-2009 global financial crisis, and it experienced no change after, for instance, the European debt crisis. The considerable shocks to the system during these episodes of crisis had predictable consequences on the banks' performance, but they did not change the nature or the shape of systemic risk. Notice that the two factors in our model measure two different sources of vulnerability in the global banking sector and for this reason, as expected, they both are significant. While the systemic risk indicator is to be interpreted as a "financial" risk shock, the EMU index quantifies "economic" uncertainty related with equity markets. This theoretical separation allows us to interpret our main findings as arising from the financial and macroeconomic (real) sides of the economic system.

We can also conclude that the impact of equity market uncertainty on the financial returns of the global banking sector is negative. This result is novel to the literature, but it is well grounded on theoretical preconceptions concerning uncertainty. Specifically, aggregate uncertainty shocks are thought to be preceded by a reduction in investment and, possibly, in labor, and, consequently, by a deterioration in real activity (Bernanke, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1996; Leahy and Whited, 1996; Caballero and Pindyck, 1996; Bloom et al., 2007; Bachmann and Bayer, 2013), which in turn has obvious consequences for banking. Moreover, this impact on macroeconomic variables may be amplified as a result of financial market frictions (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014). In the case of financial markets, Bansal and Yaron (2004) explain why markets dislike uncertainty and how more uncertainty leads to worse long-run growth prospects, thus reducing equity prices. Basically, the intuition is linked to the fact that markets do not like uncertainty and after an increment in uncertainty, the discount of the expected cash flows is higher, which leads the market to reduce the price of the stock. Here we find that higher levels of uncertainty impact negatively and significantly on the financial performance of the global banking system. We believe therefore, that market uncertainty should be included as a major force behind the systemic shocks faced by financial institutions in the global financial markets, and that it should be consistently monitored by regulators and supervisors.

B. Systemically vulnerable financial institutions

The previous literature has routinely explored the case of systemically important financial institutions or SIFIs (FSB, 2011; 2012; 2013; IAIS, 2009; 2012; 2013). Here, in contrast, we have focused on systemically vulnerable financial institutions (SVFIs), which while not unrelated, respond to a different logic. The ranking we present is constructed by taking into account the magnitude of the responses of each bank to the two systemic shocks analyzed here, which is not the same as considering which institutions are more likely to disrupt the financial system after experiencing a sizeable loss. As such, SVFIs should be seen as complementing SIFIs.

Our ranking is bi-dimensional: on the one hand, it measures the sensitivity of each bank to the unobservable systemic risk factor and, on the other, it measures their response to the equity market uncertainty factor. The responses to the former were transformed using absolute values, because the principal component estimates do not allow us to interpret the sign of the factor. In Figure 4.2, we present a scattergram of the coefficients $|\alpha_1|(\tau = 0.1)$ plotted against the coefficients $\alpha_2(\tau = 0.1)$, where $|\cdot|$ denotes the absolute value function.

The banks were then sorted on the basis of these values and classified into quartiles – that is, the banks in quadrant IV (bottom-right) are our first SVFIs candidates. These banks are the ones that respond most to both the systemic traditional shock and to the uncertainty shock. In other words, the respective coefficient for each institution in quadrant IV is lower than the vertical median of α_2 and higher than the horizontal median of α_1. In contrast, the more resilient institutions lie in quadrant I (top-left), where the responses to both economic uncertainty and the systemic risk factor are the smallest in the sample.

The further a bank is from the origin in both directions considered here, the more vulnerable it is to the shocks. For instance, if we take the banks that lie above the 90^{th} percentile in terms of α_1 and below the 10^{th} percentile in terms of α_2, we find the most vulnerable financial institutions, namely, Allied Irish Bank, Bank of Ireland, Barclays, Mediobanca (France) and Royal Bank of Scotland. In contrast, the most resilient institutions are: Bank of Montreal, Bank of Nova Scotia, Canadian Imperial Bank of Commerce and Valiant 'R'.

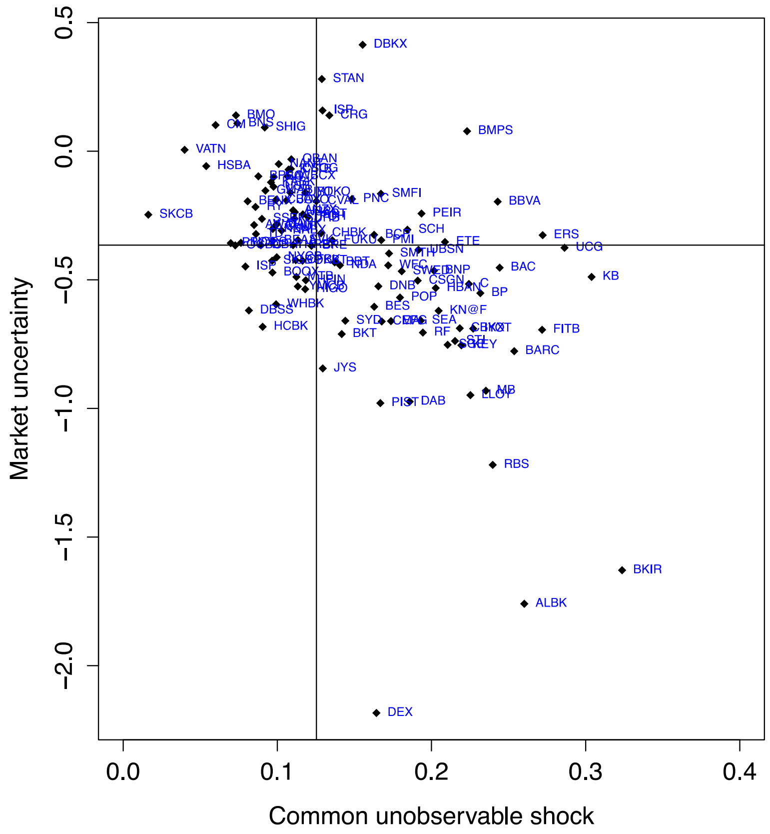


Figure 4.2. Sensitivity to the two risk factors: uncertainty and common component For each of the 113 banks making up our sample, we plotted $\alpha 2$ (τ=0.1) against $\alpha 1$ (τ=0.1). The banks located in quadrant I (top-left) are the least vulnerable to the risk factors: f_1 (common unobservable shock – horizontal axis) and f_2 (market uncertainty – vertical axis). In contrast, the banks in quadrant IV (bottom-right) are the most vulnerable following exposure to the two risk factors.

In Table 4.5, we provide a full ranking for the two dimensions. Notice that the differences between the institutions are marked. For example, if we consider a shock to (log) uncertainty of one standard deviation in the market, the most vulnerable institution in our sample, Dexia, would experience a reduction in the 10th percentile of its weekly returns distribution of around 1.77 percentage points (Dexia's average weekly return during the sample was -0.33%), while the impact is practically negligible for institutions in the fourth quartile. The median impact is around -0.30 percentage points.

The same holds for the systemic factor retrieved as an unobservable and common component of the system. In this case, the most vulnerable institution is the Bank of Ireland, and a one standard deviation shock to the systemic factor would increase its weekly VaR in the 90th percentile by 2.80

percentage points. In this case, the median impact is around 1.09 and the impact for the least vulnerable institution is around 0.18 percentage point

Table 4.5. SVFIs' ranking

Common unobservable factor								Market uncertainty factor							
Q1		Q 2		Q 3		Q4		Q 1		Q 2		Q 3		Q 4	
BKIR	0.32	CSGN	0.19	CVAL	0.13	CHUT	0.10	DEX	-2.18	BP	-0.55	HRBK	-0.37	BENX	-0.19
KB	0.30	DAB	0.19	BPE	0.12	NA	0.10	ALBK	-1.76	HIGO	-0.54	PBCT	-0.36	CVAL	-0.19
UCG	0.29	SCH	0.18	POH	0.12	USB	0.10	BKIR	-1.63	HBAN	-0.53	UOBS	-0.36	JOYO	-0.19
ERS	0.27	SWED	0.18	HFIN	0.12	BEAA	0.10	RBS	-1.22	YMCB	-0.53	ETE	-0.35	CBAX	-0.19
FITB	0.27	POP	0.18	YOKO	0.12	NSHI	0.10	PIST	-0.98	DNB	-0.53	BEAA	-0.35	PNC	-0.19
ALBK	0.26	EFG	0.17	HIGO	0.12	BOQX	0.10	DAB	-0.97	C	-0.52	FUKU	-0.35	SMFI	-0.17
BARC	0.25	SMTH	0.17	HABT	0.12	SIGB	0.10	LLOY	-0.95	CSGN	-0.5	PMI	-0.35	JURT	-0.16
BAC	0.24	WFC	0.17	OKBT	0.12	KABK	0.10	MB	-0.93	HFIN	-0.5	SVK	-0.35	YOKO	-0.16
BBVA	0.24	CMA	0.17	SVK	0.11	GMAB	0.09	JYS	-0.84	MTB	-0.49	ERS	-0.33	GMAB	-0.15
RBS	0.24	PMI	0.17	YMCB	0.11	SHIG	0.09	BARC	-0.78	KB	-0.49	BCP	-0.33	USB	-0.14
MB	0.24	SMFI	0.17	MTB	0.11	HCBK	0.09	KEY	-0.75	BOQX	-0.47	TD	-0.32	KABK	-0.12
BP	0.23	PIST	0.17	OFBK	0.11	SSBK	0.09	SGE	-0.75	SWED	-0.47	CHBK	-0.32	NA	-0.1
IYOT	0.23	DNB	0.17	HSBC	0.11	DBHI	0.09	STI	-0.74	BNP	-0.46	NABX	-0.31	BPSO	-0.1
LLOY	0.23	DEX	0.16	SURB	0.11	BPSO	0.09	BKT	-0.71	BAC	-0.45	SCH	-0.31	WBCX	-0.1
C	0.22	BES	0.16	ANZX	0.11	TD	0.09	RF	-0.7	ISP	-0.45	NSHI	-0.3	KYTB	-0.07
BMPS	0.22	BCP	0.16	HRBK	0.11	RY	0.09	FITB	-0.69	WFC	-0.44	CHUT	-0.29	CSOG	-0.07
KEY	0.22	DBKX	0.16	OBAN	0.11	AWAT	0.08	IYOT	-0.69	NDA	-0.44	AWAT	-0.29	HSBA	-0.06
CBKX	0.22	PNC	0.15	CSOG	0.11	DBSS	0.08	CBKX	-0.69	BBT	-0.43	DANK	-0.28	NANT	-0.05
STI	0.22	SYD	0.14	JURT	0.11	BENX	0.08	HCBK	-0.68	OKBT	-0.43	SSBK	-0.26	OBAN	-0.03
SGE	0.21	BKT	0.14	KYTB	0.11	ISP	0.08	CMA	-0.66	SIGB	-0.43	SURB	-0.26	VATN	0.01
ETE	0.21	NDA	0.14	WBCX	0.11	UOBS	0.08	EFG	-0.66	OFBK	-0.42	POH	-0.26	BMPS	0.08
KN@F	0.20	BBT	0.14	JOYO	0.11	BNS	0.07	SYD	-0.66	NYCB	-0.41	SKCB	-0.25	SHIG	0.09
HBAN	0.20	FUKU	0.14	NABX	0.10	BMO	0.07	SEA	-0.66	SMTH	-0.4	HABT	-0.25	CM	0.1
BNP	0.20	CRG	0.13	NANT	0.10	OCBC	0.07	KN@F	-0.62	UBSN	-0.38	PEIR	-0.24	BNS	0.11
RF	0.19	JYS	0.13	DANK	0.10	PBCT	0.07	DBSS	-0.62	UCG	-0.38	HSBC	-0.24	CRG	0.14
PEIR	0.19	ISP	0.13	NYCB	0.10	CM	0.06	BES	-0.6	BPE	-0.37	ANZX	-0.23	BMO	0.14
SEA	0.19	STAN	0.13	WHBK	0.10	HSBA	0.05	WHBK	-0.6	OCBC	-0.37	RY	-0.22	ISP	0.16
UBSN	0.19	CHBK	0.13	CBAX	0.10	VATN	0.04	POP	-0.57	DBHI	-0.37	BBVA	-0.2	STAN	0.28
						SKCB	0.02							DBKX	0.41

Note: In the first eight columns we provided the ranking of the institutions according to factor f_1, the common unobservable shock (in absolute values). We discriminated in each couple of columns between the quartiles of the ranking. In last eight columns we ordered from most sensitive to least sensitive the banks in our sample, according to f_2, the uncertainty factor. Again we separated in quartiles of 28-29 banks.

We believe this ranking of SVFIs should be useful for regulators as well as for bank administrators since it provides new information when measuring the resilience of institutions to systemic shocks.

C. Comparisons with marginal expected shortfall (MES)

In this section we compare our two dimensions of systemic risk with the MES proposed by Achayra et al. (2016). Recall that MES is defined as the bank's losses in the tail of the system's loss distribution and as such it is intended to measure the expected contribution to systemic risk of a particular bank, during episodes of financial distress. Therefore, our estimates, which are based on the quantiles of the banks' return distributions, instead of those of the system, can be thought of as natural complements in the analysis of systemic risk. Notice that in our case we have a direct estimation of the system's outcome, namely, the common unobservable market factor, calculated as the first principal component of our data set. Therefore, the construction of the MSE is straightforward: We average the banks' returns observed at the 5% lower tail of the market factor distribution.

In Figure 4.3 we plot the MES against the market factor (left) and the economic uncertainty factor (right). As it can be seen, the market factor and MES display a negative and clear relationship. Indeed, the coefficient of determination when we regress the market factor slopes on MES, is equal to 79.6%, and the slope of the regression (-3.8) is statistically significant at 99% level of confidence. This strong relationship is expectable although is not obvious. On the one hand MES is conditioned on the quantiles of the system, while in the other hand the market factor slopes are conditioned on the banks' quantiles. Also, there is around 20% of the variation in our measure that is not captured by the MSE.

The case for the uncertainty factor is even clearer. There is a positive relationship between the slopes associated to uncertainty and MES. In this case we document, once again, a statistically significant slope (12.9) at 99% of confidence, but now $R^2 = 25.1\%$. Thus, more or less 75% of the information provided by the uncertainty factor is not captured by MES.

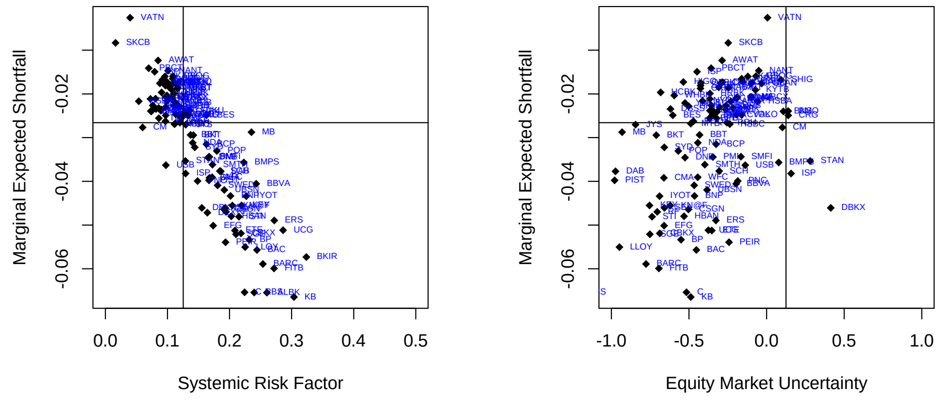


Figure 4.3: Relationship between the market factor and MES (left) and the uncertainty factor and MES (right). For each of the 113 banks making up our sample, we plotted α2 (τ=0.1) against MES and α1 (τ=0.1) against MES. The banks located in quadrant I (top-left) are the least vulnerable to the risk factors. In contrast, the banks in quadrant IV (bottom-right) are the most vulnerable following exposure to the two risk factors.

Regulators are generally interested not only on the level of exposure to the systemic risk factors, but also in generating rankings among the institutions on these grounds. Once again, there is more information, otherwise absent, that we can assess using our proposed systemic factors. In Table 4.6 we present the first 11 institutions in each ranking, according to the three factors. That is, the 10% most vulnerable institutions. As can be noted, only 3 institutions belong to the three sets. Also the order is different in each ranking, indeed, not single bank in Table 4.5 remains in the same position of the three rankings. When we expand the analysis to the first quartile of the banks (28 institutions), 85.7% of those banks that belong to the first quartile of the MES' ranking also belong to the first quartile according to the market factor sensitivity; on the other side, 57.1% of those in the uncertainty ranking belong as well to the most vulnerable institutions according to MES.

Table 4.5

Institutions' ranking according to different criteria

Market	Uncertainty	MSE
BKIR	DEX	KB
KB	**ALBK**	**ALBK**
UCG	**BKIR**	RBS
ERS	RBS	C
FITB	PIST	FITB
ALBK	DAB	**BARC**
BARC	LLOY	**BKIR**
BAC	MB	BAC
BBVA	JYS	LLOY
RBS	**BARC**	PEIR
MB	KEY	BP

Note: In the columns we provided the ranking of the institutions according to the market factor, the uncertainty factor and the MES. The bolded institutions belong to the 10% most vulnerable set according to the three measures.

4.6. Conclusions

We measure systemic risk in the global banking sector attributable to two main sources: an unobservable common shock to the market, previously identified in the literature as a financial systemic shock, and an economic uncertainty factor in the equity market. The two measures are, in most instances, statistically significant in terms of explaining systemic risk, above all during the final regime of our sample. The two factors in our model measure two different sources of vulnerability in the global banking sector and for this reason, as expected, they both remain significant within the model. While the systemic risk indicator is to be interpreted as a "financial" risk shock, the economic equity market uncertainty index reflects "economic" uncertainty related with the equity market. This theoretical separation allows us to interpret our main findings as arising from the financial and macroeconomic (real) sides of the economic system.

We are able to identify regimes after conducting a recursive search for structural changes in the model's parameters. This allows us to test explicitly for the stability of systemic risk propagation in the global banking sector. We found that the parameters containing the expected impact of a given shock to the system on the financial institutions have not experienced any significant changes over the last decade, above all after and during the 2007-2009 global financial crisis. We interpret this as evidence of claims that during the financial crisis the economy was not affected by a new type of shock, but rather the shocks were of the same nature, albeit of an unusually high magnitude.

We also provide a ranking of systemically vulnerable financial institutions, which serves to complement existing alternatives in the literature and allows regulators and administrators alike to identify the banks that are most vulnerable to the types of shock analyzed here.

Yet, inevitably, further research is required. Here, for example, we only consider the impact of contemporaneous systemic shocks on the system – that is, we do not estimate a dynamic model for each financial institution, which would clearly help enrich any description of the system's dynamics. The construction of dynamic lagged functions in this regard is critical, but the approach has yet to be resolved when employing quantile regressions. We leave this for future research.

We recognize that it is always possible to include other candidates as systemic shocks, in addition to that of equity market uncertainty. For example, traditional proxies based on CDS, sovereign credit risk, interbank exposures, liquidity ratios, or even other indices of policy uncertainty could be explored. We consider our proposal as representing one step in the direction of explaining systemic risk, and believe uncertainty to be one of the first natural candidates for consideration as a systemic shock. Eventually, any unobservable factor should optimally be replaced by more clearly identifiable factors identified in the literature.

Appendix to Chapter 4

Table A
Non-banking firms in the sample

INSURANCE		OTHER	
NAME	**NAME**	**NAME**	**NAME**
ACE	MANULIFE FINANCIAL	3I GROUP	MAN GROUP
AEGON	MAPFRE	ABERDEEN ASSET MAN.	MARFIN INV.GP.HDG.
AFLAC	MARKEL	ACKERMANS & VAN HAAREN	MITSUB.UFJ LSE.& FINANCE
AGEAS (EX-FORTIS)	MARSH & MCLENNAN	ACOM	MOODY'S
ALLIANZ (XET)	MS&AD INSURANCE GP.HDG.	AMERICAN EXPRESS	MORGAN STANLEY
ALLSTATE	MUENCHENER RUCK. (XET)	ASX	NOMURA HDG.
AMERICAN INTL.GP.	OLD MUTUAL	BANK OF NEW YORK MELLON	NORTHERN TRUST
AMLIN	PARTNERRE	BLACKROCK	ORIX
AMP	POWER CORP.CANADA	CHARLES SCHWAB	PARGESA 'B'
AON CLASS A	POWER FINL.	CHINA EVERBRIGHT	PERPETUAL
ARCH CAP.GP.	PROGRESSIVE OHIO	CI FINANCIAL	PROVIDENT FINANCIAL
ASSICURAZIONI GENERALI	PRUDENTIAL	CLOSE BROTHERS GROUP	RATOS 'B'
AVIVA	QBE INSURANCE GROUP	COMPUTERSHARE	SCHRODERS

AXA	RENAISSANCERE HDG.	CREDIT SAISON	SLM
AXA ASIA PACIFIC HDG.	RSA INSURANCE GROUP	DAIWA SECURITIES GROUP	SOFINA
CHALLENGER	SAMPO 'A'	EATON VANCE NV.	STATE STREET
CHUBB	SCOR SE	EQUIFAX	SUNCORP GROUP
CINCINNATI FINL.	STOREBRAND	EURAZEO	T ROWE PRICE GROUP
CNP ASSURANCES	SWISS LIFE HOLDING	FRANKLIN RESOURCES	TD AMERITRADE HOLDING
EVEREST RE GP.	SWISS RE 'R'	GAM HOLDING	WENDEL
FAIRFAX FINL.HDG.	TOPDANMARK	GBL NEW	
GREAT WEST LIFECO	TORCHMARK	GOLDMAN SACHS GP.	
HANNOVER RUCK. (XET)	TRAVELERS COS.	ICAP	
HARTFORD FINL.SVS.GP.	UNUM GROUP	IGM FINL.	
HELVETIA HOLDING N	VIENNA INSURANCE GROUP A	INDUSTRIVARDEN 'A'	
ING GROEP GDR	W R BERKLEY	INTERMEDIATE CAPITAL GP.	
JARDINE LLOYD THOMPSON	XL GROUP	INVESTOR 'B'	
LEGAL & GENERAL	ZURICH FINL.SVS. (IRS)	KINNEVIK 'B'	
LINCOLN NATIONAL	ZURICH INSURANCE GROUP	LEGG MASON	
LOEWS		MACQUARIE GROUP	

Note: The sector classification used in the sample includes Banks, Asset Management, Specialty Finance, Investment Service, Consumer Finance, Financial Administration, Life Insurance, Property and Casualty Insurance, Full Line Insurance, Insurance Broker, and Reinsurance. Although all the institutions were used to estimate the systemic factor, only the banks were used to estimate the systemic risk models. Data and classification were taken from Datastream.

Chapter 5: Currency downside risk, liquidity, and financial stability

Abstract

We estimate volatility- and quantile (depreciation)-based spillovers across 20 global currencies against the US Dollar. In so doing, we reveal significant asymmetries in the propagation of risk across global currency markets. The quantile-based statistic reacts more significantly to events that have a sizable impact on FX markets (e.g. Brexit vote and the FX crash following the subprime crisis), and which are missed by the volatility- and return-based statistics. As such, our tail-spillover estimates constitute a new financial stability index for the FX market. This index has the advantages of being easy to build, of not requiring intraday data and of being more informative about currency crises and pressures than traditional spillover statistics based on volatilities. Finally, we also document differences in the relation between both liquidity and volatility and quantile spillovers, respectively.

5.1. Introduction

Currency crises have been of particular concern for policy-makers, regulators, practitioners and academics since at least the post-Bretton Woods era (Krugman, 2000). In the intervening years, one of the most frequently examined – albeit one of the least understood – issues related to such crises have been the mechanisms of propagation of currency shocks, be they a consequence of macro-fundamentals, coordinated polices, common-lenders, speculative attacks or simply a result of unexpected (or unexplained) mechanisms (pure-contagion)[34]. Yet, co-movements and risk spillovers in currency markets can have an enormous economic and social impact on financial and macroeconomic stability and, hence, on wellbeing[35]. Currency shock spillovers have been shown to be closely linked to global imbalances, investor speculation, sovereign debt concerns (Chen, 2014), sudden stops, sharp real depreciations and asset price crashes (Apostolakis and Papadopoulos, 2015; Korinek and Mendoza, 2014) and, therefore, to financial collapses. Currency trading, measured in dollar volume, represents the largest financial market on the planet: an average of $5.1 trillion each day according to the latest Triennial Central Bank Survey conducted by the Bank for International Settlements (Bank of International Settlements, 2016). Hence, understanding spillovers in foreign exchange (FX) markets is critical for maintaining financial stability.

[34] See Rigobon (2002) and references therein for a discussion about contagion, including currency markets.

[35] See Krugman (2000) and references therein.

There is a well-established branch of the macro-financial literature that empirically studies spillovers in FX markets (Hong, 2001; Melvin and Peiers, 2003; Cai et al., 2008; Bekiros and Diks, 2008; Bubák et al., 2011; Li, 2011; Antonakakis, 2012; Kavli and Kotzé, 2014; Diebold and Yilmaz, 2015; Greenwood-Nimmo et al., 2016). Some of these studies focus specifically on spillovers between highly traded currencies (for instance, Greenwood-Nimmo et al., 2016) while others also include emerging market currencies with lower trade volumes (e.g. Kavli and Kotzé, 2014).

The study of return and volatility spillovers in currency markets imposes its own symmetry on the analysis, by implicitly assuming that for any given country that the situation is roughly the equivalent of facing depreciation or appreciation pressures[36]. This assumption is at the very least controversial. In the worst-case scenario, central banks may *lean against the wind* when appreciation pressures emerge on the horizon, to the degree that they are willing (or politically allowed) to do so. On the other hand, their response is much more restricted when faced by an episode of depreciation. Here, in the worst case they are bound by the (frighteningly) lower limit of the FX reserves.

The aim of this paper is to analyze *downside* risk propagation across global currency markets and the ways in which it is related to liquidity. We make two primary contributions to the literature. First, we estimate *tail-spillovers* between currencies in the global FX market. Unlike previous studies that focus on return co-movements and volatility spillovers in currency markets, we directly address the issue of risk spillovers in the left tail of the daily variations in currency prices (depreciations). We do so by closely adhering to what we consider a key element in the definition of a currency crisis proposed by Paul Krugman: "[it] is a sort of circular logic, in which investors flee a currency because they fear that it might be *devalued*, and in which much (though not necessarily all) of the pressure for such a *devaluation* comes precisely from that capital flight" (Krugman, 2000, p 1. The emphasis is ours). Notice that by definition currency crises are related to periods of depreciation (or devaluation), and not to episodes of appreciation (or revaluation). Thus, in terms of financial stability, episodes of depreciation are more significant than those of appreciation. Our strategy allows us to consider specifically *downside risk* in currency markets, corresponding in this instance to episodes of *depreciation* of the global currencies against the US dollar. This is more consistent with the definition of a currency crisis. Moreover, our tail-spillover

[36] The importance, on empirical grounds, of considering asymmetries when modeling exchange rate variations has been documented for instance by Patton (2006) and Reboredo et al. (2016). Unlike the analysis reported herein, these studies neither consider dynamic spillovers nor focus on currency crises and systemic risk, rather they model pairs of series – the Deutsche Mark and US Dollar in the former case and stock returns against exchange rates for emerging economies in the latter.

estimates can be used to construct a new financial stability index for the FX market. This index is easy to build and does not require intraday data, which constitutes an important advantage. Our second contribution is that we explore whether turnover is related to risk spillovers in global currency markets. In this respect we draw inspiration from Mancini et al. (2013) and Karnaukh et al. (2015), who document a significant relationship between currency liquidities (i.e. commonality). Our intuition is that liquidity matters for spillovers. World currencies can be expected to behave differently depending on how much investors trade them and, in turn, commonality may become evident by examining the dynamic spillovers in worldwide FX markets.

In line with Diebold and Yilmaz (2015), we opted to include in our sample of 20 currencies against the US dollar those with high trading volume ratios (Euro, Yen, British Pound, Australian Dollar, Canadian Dollar, Swiss Franc, Swedish Krona, Mexican Peso, New Zealand Dollar, Singapore Dollar, and Norwegian Krone) as well as those with considerably lower market transaction levels (South Korean Won, Turkish Lira, Indian Rupiah, Brazilian Real, South African Rand, Polish Zloty, Thai Baht, Colombian and Philippine Pesos). In this way, we seek to provide a more comprehensive panorama of global FX market dynamics.

Our methodology consists of two steps. First, we estimate intraday range volatilities and conditional quantiles. Then we use these series as input to construct traditional Diebold and Yilmaz (2012, 2014) statistics, net pairwise statistics and networks. Obvious alternatives for constructing asymmetric spillovers are semi-variances, as performed by Barndorff-Nielsen et al. (2010). However, these semi-variances, especially the measure of 'bad volatility', are based on 'fill-in asymptotics', and require intraday prices to be constructed on a daily basis. Our measure is based on conditional quantiles and does not require this level of detailed information. Second, our measure focuses specifically on a high quantile (95th percentile), as opposed to the full spectrum of 'bad volatility', which refers approximately to 50% of the variations. It is our contention that the two steps outlined above represent compelling advantages of our proposal.

We document significant asymmetries in terms of risk propagation that become evident after comparing volatility-based and quantile-based spillover measures. The quantile-based statistic reacts more significantly to events that have a sizable impact on FX markets (e.g. the Brexit vote and the FX crash following the subprime crisis), and which are missed by the volatility- and return-based statistics. We also gain insights into the relation between liquidity and spillovers. For example, while Karnaukh et al. (2015) document that the most liquid currencies are more strongly affected by global risk factors during turbulent times, we complement this analysis by showing that during the subprime crisis and its aftermath (between 2008 and 2012) the most liquid currencies not only behaved as net-receivers of volatility shocks (in this respect in line with Karnaukh et al., 2015), but also that this pattern is reversed for the period 2012-2016, indicating that the most liquid currencies are also able to destabilize the rest of the market during episodes of relative calm. Interestingly, the shocks propagate as in *a cascade*: the more liquid a set of currencies is, the more likely *it affects* all the other currencies, *during periods of depreciation* (against the USD). Conversely, the more liquid it is, the more likely *it is affected* by all the other currencies *during turbulent periods that lack a clear trend* in terms of appreciation or depreciation.

Our analyses provide new perspectives on the relation between liquidity and volatility (quantile) spillovers. In the case of tail-spillovers, most liquid currencies are, by rule, net-receivers and the least liquid currencies are net-transmitters. However, in the case of volatility spillovers, the (receiving or transmitting) role of the currencies is sorted by liquidity changes during periods of depreciation, appreciation or turbulence.

The significant asymmetries that we reveal by contrasting quantile- and volatility-based measures of spillovers are critical for financial stability, and should be taken into consideration when conducting exercises that seek to monitor financial fragility around the world. Our findings are also relevant for designing the hedging mechanisms that are of such instrumental importance for international investors.

The rest of the paper is organized as follows. Section 2 presents the methodological approach we adopt and section 3 describes our data. The results of the spillover analysis are discussed in section 4 and section 5 concludes.

5.2. Methodology

We used variance decomposition of forecast errors, as proposed by Diebold and Yilmaz (2012), to analyze spillovers between range-based volatilities and between quantiles of daily log-variations in foreign exchange markets. To estimate the latter, we employed an asymmetric slope Conditional Autoregressive Value at Risk model (CAViaR) as introduced by Engle and Manganelli (2004). We also used graphical networks to analyze specific dates in the foreign exchange markets, in line with Diebold and Yilmaz (2014).

A. Volatility Measure

We calculated the volatilities of each of the 20 currencies using the range-based volatility framework proposed by Parkinson (1980). We opted for this framework given its efficiency and simplicity both of estimation and interpretation (Alizadeh et al., 2002). The daily variance of each market *i* is calculated based on the highest and lowest daily prices on day *t* as follows:

$$\bar{\sigma}_{it}^2 = 0.361[\ln Pmax_{it} - \ln Pmin_{it}]^2, \tag{5.1}$$

where $Pmax$ is the highest price of currency *i* on day *t* and $Pmin$ is the lowest price of currency *i* on day *t* for $i = 1, \dots N$ and $t = 1, \dots, T$. The annualized volatility in percentage points was calculated as:

$$\tilde{\sigma}_{it}^2 = 100\sqrt{365\, \bar{\sigma}_{it}^2}. \tag{5.2}$$

B. CAViaR model

The CAViaR model for variable y_t can be expressed as:

$$q_t(\beta, \alpha) = \delta_0(\alpha) + \sum_{i=1}^{s} \delta_i(\beta, \alpha)\, q_{t-i}(\alpha) + \sum_{j=1}^{p} \gamma_j(\alpha)\, F(x_{t-j}, \omega), \tag{5.3}$$

where α is the level of confidence of the associated VaR, x_t are the variables on which we condition the estimation of the quantile, β is a vector of unknown parameters of size *p*, ω is the information set, and $q_t(\beta, \alpha)$ is the α quantile at time *t* of the variable y_t, which in our case corresponds to the daily log variation of each FX in our sample. The second term in the equation relates to the autoregressive component that allows for the smooth dynamics of the quantile, while the third term is related to the conditioning variables. Specifically, the asymmetric slope CAViaR can be expressed as:

$$q_t(\beta, \alpha) = \beta_0(\alpha) + \beta_1(\alpha) q_{t-i}(\beta, \alpha) + \beta_2(\alpha) {y_{t-1}}^{-} + \beta_3(\alpha) {y_{t-1}}^{+}, \tag{5.4}$$

where ${y_t}^{-}$ and ${y_t}^{+}$ are the negative and positive values of y_t, respectively. This specification captures the asymmetric effect in the slope of the quantile, conditional on the value and on the sign of the returns.

The CAViaR model was estimated following the quantile regression framework provided by Koenker and Bassett (1978). In this framework, the parameters are estimated as a special case of the least absolute deviation (LAD) estimator. The maximization of the likelihood function was performed using numerical methods (BFGS quasi-Newton with Hessian updates).

C. Spillover measures

The spillover indices are based on a VAR with *N=20* variables, and were built on the associated forecast error variance decomposition (FEVD). The errors were estimated from the moving average representation of the VAR as follows:

$$X_t = \Theta(L)\varepsilon_t, \tag{5.5}$$

$$X_t = \sum_{t=0}^{\infty} A_i \varepsilon_{t-i}, \tag{5.6}$$

where X_t is a matriz $T \times N$, $\Theta(L) = (I - \phi(L))^{-1}$ and $A_i = \phi A_{i-1} + \phi A_{i-2} + \cdots + \phi A_{i-p}$ is the parameters' matrix, *p* is the number of lags used in the estimation, and *T* is the number of periods. To estimate the FEVD from the h-step ahead forecast, we first had to identify the structural VAR innovations by imposing restrictions on the MA parameters. In line with Diebold and Yilmaz's suggestion (2012), we followed the eclectic path proposed by Koop et al. (1996) and Pesaran and Shin (1998), namely the generalized VAR, for the construction of the FEVD.

The errors in the FEVD can be divided into *own variance* shares or *cross variance* shares. The former are the fractions of the errors that are related to a shock to x_i on itself, while the latter are the portion of the shocks on x_i related to the rest of the variables in the system. The h-step ahead FEVD can be defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i{}' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i{}' A_h \Sigma A_h{}' e_i)}, \tag{5.7}$$

where Σ is the variance matrix of ε_t, σ_{jj} is the standard deviation of the *j*-th equation, and e_j is a selection vector, with ones in the *i*-th element and zero otherwise. To guarantee that the sum of each row is 1, $\sum_j \theta_{ij}(H) = 1$, each entry of the variance decomposition must be normalized as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{H-1} \theta_{ij}(H)}. \tag{5.8}$$

With the normalized variance decomposition, a total spillover index can be calculated as:

$$C(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100. \tag{5.9}$$

This index measures the percentage variance that can be explained by cross-spillovers. It can be extended to a dynamic version, known in the literature as a *directional spillover* index, in which the effect of a shock to x_j on the variable x_i, for every period, is given by:

$$C_{i*}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100, \tag{5.10}$$

conversely, a shock to x_i on x_j is given by:

$$C_{*i}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100, \tag{5.11}$$

with the two directional spillover indices we construct a *net spillover* index, given by:

$$C_i(H) = C_{*i}(H) - C_{i*}(H). \tag{5.12}$$

The net spillover index is a measure of the effect related to a shock in the variable x_i on the rest of the system. Therefore, each variable will be either a *net receiver* or a *net transmitter* of shocks in each period. It is also possible to construct a *net pairwise spillover* index, that accounts for the net spillover effect of the exchange rate x_i on x_j, where $i \neq j$. The net pairwise index can be defined as:

$$C_{ij}(H) = \frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100. \tag{5.13}$$

D. Networks

In line with Diebold and Yilmaz (2014, 2015), we also employed graphical network analysis. Unlike those authors, we used graphs to highlight the differences between volatility-based and quantile-based measures in FX markets. Nodes and edges constitute network graphs: the former given by a certain currency and weighted according to the turnover of this currency during the last year in the sample; and the latter by the net pairwise spillover indices on a certain date. In Figure 5.5 we only include the highest quartile of the net pairwise statistics so as to better appreciate the main results.

5.3. Data

We use a database comprising twenty of the most traded currencies per US dollar (currency/US dollar) that have either a free floating, floating or managed floating exchange rate regime (see Table 5.1). Currency selection was based on the information provided by the Bank of International Settlements' Triennial Central Bank Survey of foreign exchange and OTC derivatives markets (Bank of International Settlements, 2016). This report ranks foreign exchange currencies according to their daily turnover. The exchange rate regime for each of the currencies was obtained from the International Monetary Fund's Annual Report on Exchange Arrangements and Exchange Restrictions (International Monetary Fund, 2014).

We retrieved the data that correspond to the close, high and low quotes of the exchange rates from Bloomberg. Our data span the period January 1, 2003 to September 5, 2016, for a total of 3,569 daily observations for each of the currencies. The year 2003 was chosen as the starting date in order to include in our database emerging market currencies (including the Colombian Peso and the Polish Zloty) that did not adopt a floating or managed floating exchange rate regime until around this date. We omit countries with fixed exchange rate regimes because their artificially low exchange rate risk would bias the results.

Table 5.1. Selected currencies ordered according to turnover

Code	Currency	Country	Exchange Regime
EUR	Euro	Europe	Free Floating
JPY	Yen	Japan	Free Floating
GBP	Pound Sterling	United Kingdom	Free Floating
AUD	Australian Dollar	Australia	Free Floating
CAD	Canadian Dollar	Canada	Free Floating
CHF	Franc	Switzerland	Managed Floating
SEK	Swedish Krona	Sweden	Free Floating
MXN	Mexican Peso	Mexico	Free Floating
NZD	New Zealand Dollar	New Zealand	Floating
SGD	Singapore Dollar	Singapore	Managed Floating
NOK	Norwegian Krone	Norway	Free Floating
KRW	Won	South Korea	Floating
TRY	Lira	Turkey	Floating
INR	Rupee	India	Floating
BRL	Real	Brazil	Floating
ZAR	Rand	South Africa	Floating
PLN	Zloty	Poland	Free Floating
THB	Baht	Thailand	Floating
COP	Colombian Peso	Colombia	Floating
PHP	Philippine Peso	Philippines	Floating

Source: Bank of International Settlements (2016) and International Monetary Fund (2014).

A. Descriptive statistics of daily log variations in FX markets

Table 5.2 provides the summary statistics of the annualized FX log returns in our sample. In Tables A1 and A3 in the appendix, we provide the descriptive statistics for the estimated volatilities and VaRs. FX returns are characterized by heavy tails and some by negative skewness. The ZAR displays the highest one-day depreciation in the sample, with a 15 percent drop in October 2008. The range (difference between daily max. and min.) of the currencies of the developing economies and the commodity exporting countries is, in general, greater than that of the currencies of the developed economies. Consistent with this, the former currencies present higher risk, with a greater standard deviation, than that presented by the mature markets.

Table 5.2.
Summary statistics of annualized FX log returns

Our data span January 1, 2003-September 5, 2016. We use a database comprising twenty of the most traded currencies per US dollar (currency/US dollar) that have either a free floating, floating or managed floating exchange rate regime.

	EUR	JPY	GBP	AUD	CAD	CHF*	SEK	MXN	NZD	SGD
Mean	0.03	0.04	0.00	0.08	0.05	0.08	0.04	-0.03	0.08	0.03
Median	0.03	0.00	0.00	0.14	0.04	0.00	0.03	0.04	0.14	0.06
Maximum	13.42	14.92	11.27	35.25	15.64	103.58	20.20	27.45	17.09	7.28
Minimum	-8.50	-18.12	-26.40	-23.38	-11.19	-28.25	-14.30	-22.57	-21.81	-7.89
Std. Dev.	2.29	2.36	2.16	3.10	2.24	3.05	2.89	2.61	3.12	1.13
Skewness	0.19	0.27	-0.66	0.18	0.03	10.96	0.18	-0.16	-0.14	-0.30
Kurtosis	4.80	7.25	11.12	13.80	5.51	378.48*	5.92	12.96	5.37	7.48
	NOK	**KRW**	**TRY**	**INR**	**BRL**	**ZAR**	**PLN**	**THB**	**COP**	**PHP**
Mean	0.02	0.04	-0.01	-0.02	0.08	0.03	0.06	0.03	0.04	0.02
Median	0.00	0.04	0.12	0.00	0.00	0.07	0.11	0.00	0.00	0.00
Maximum	19.67	37.33	25.89	13.51	32.25	28.56	26.28	14.09	31.92	8.10
Minimum	-16.26	-25.32	-23.92	-10.95	-21.23	-43.22	-16.87	-22.64	-22.10	-9.28
Std. Dev.	2.92	2.71	3.17	1.69	3.75	4.10	3.41	1.56	2.86	1.40
Skewness	0.03	1.11	-0.26	0.05	0.16	-0.32	0.08	-0.87	0.53	-0.02
Kurtosis	5.52	31.03	9.23	9.24	8.40	9.18	6.97	32.21	14.04	5.24

*In September 2011, the Swiss National Bank adopted a fixed exchange rate with the Euro and, subsequently, in January 2015, it abandoned the peg. These two episodes explain the abnormal maximum, kurtosis and skewness of the Swiss Franc (CHF). Except for these episodes, the CHF is remarkably stable, with a standard deviation of 2.46, a skewness of 0.37, and a kurtosis of 6.54. We include it in our sample due to its historical and financial importance as a 'haven' currency.

B. Trends in currency markets

Figure 5.1 presents a subsample of three high- and three low-traded currencies against the US Dollar from January 1, 2003 to September 5, 2016. The period from the beginning of the sample until July 2008 features a general depreciation of the US dollar. However, the period from August 2008 to May 2012 is more difficult to characterize. Thus, while the US dollar was depreciating against AUS, JPY and BRL, it recorded various changes in terms of appreciation and depreciation against EUR, TRY and MXN. Caballero, Farhi, and Gourinchas (2008) document a significant flow of capital across the global economy during this period, which helps to explain the turbulence observed. Basically, the subprime crisis created an abnormal demand for higher returns outside the main markets (i.e. in the emerging and commodity markets), which in turn fostered a higher demand for the foreign currencies of net-exporters of commodities. The last period in the sample – from June 2012 until September 2016 – was characterized by an appreciation of the US Dollar (although one exception to this pattern was Japan at the end of the sample). This US appreciation followed on from the events of the 2010 European debt crisis; the sharp fall in commodity prices at the end of 2011, and the crises faced by such countries as Greece (May 2010), Ireland (November 2010), and Portugal (May 2011), which subsequently escalated to affect Cyprus (December 2011) and Spain (July 2012). The final years in the sample were also characterized by the progressive recovery of the US economy.

This raw characterization, which identifies the depreciation of the US Dollar from 2003 to 2007, a period of turbulence from 2008 to 2012, and a period of appreciation from 2013 onwards, also provides a reasonable fit with the behavior of the other exchange rates in our sample, but that are not included in the plot. We use this characterization below to describe some of our results.

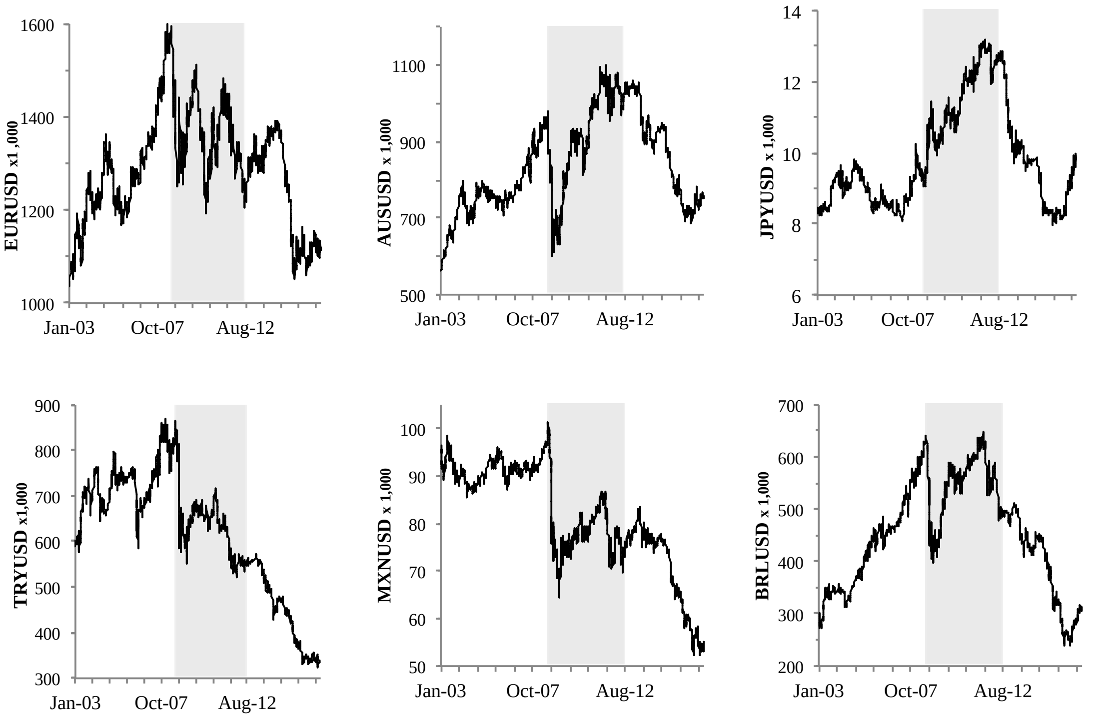


Figure 5.1. Subsample of three high- and three low-traded currencies against US Dollar. The figure illustrates the behavior of the exchange rates in both mature (top row) and emerging (bottom row) economies. The period from the beginning of the sample until July 2008 is characterized, in general, by the depreciation of the US dollar (the Mexican Peso being an exception). The period from August 2008 to May 2012 is difficult to characterize, while the US dollar was depreciating against AUS, JPY and BRL, it recorded marked changes against EUR, TRY and MXN. As such, it can be labelled as a period of turbulence. Finally, from June 2012 until the end of the sample in September 2016, there was a general appreciation of the US Dollar (with Japan being one exception at the end of the sample). This characterization also fits reasonably well with the behavior of the other exchange rates in our sample. Our data span January 1, 2003- September 5, 2016.

5.4. Results

We organize our results in four sections. First, we describe the variance-decomposition exercise using the full sample, and both the log-volatility and log-quantile statistics. Second, we present our systemic index of financial fragility in global currency markets, and we compare it with a more traditional index based on volatility spillovers, similar to that proposed by Diebold and Yilmaz (2015) and which is updated regularly on their web page[37]. Third, in seeking to emphasize the differences between volatility and tail spillovers, we analyze two recent, relevant dates in the global currency market in terms of financial stability using graphical network representations. Finally, we show how turnover as a measure of liquidity helps us understand the way in which currency shocks propagate in the market.

A. Static variance decomposition of currency shocks: volatilities versus left tails

In Tables 5.3 and 5.4, we show the 10-day-ahead variance decomposition of our two specifications. The currencies are organized from left to right (and from top to bottom) according to their turnover. The greatest turnover in the sample is displayed by the Euro-USD pair (EUR/USD), 31.3% of the total, while the lowest turnover is associated with the Philippine Peso, 0.1% of the total, according to the Bank of International Settlements (2016). This exercise is useful for identifying currencies with a high capacity to destabilize global currency markets, by generating significant shocks to the rest of the system. It also allows us to identify the most vulnerable currency pairs in our sample.

Several common patterns emerge from a comparison of the two tables. For example, the least liquid currencies in the sample are neither transmitters nor receivers in absolute terms. COP, THB and PHP display the greatest percentage of variability arising from their own shocks, both in terms of volatility and depreciation-VaRs. Various other currencies, while more liquid, present evidence of a similar behavior. This is the case of INR and SGD (especially in volatilities). None of these markets transmits (receives) a shock to (from) any other market above 7.0%[38].

We also observe that TRY and PLN tend to transmit shocks to the market above 7.0% and, in all circumstances, more frequently than they receive shocks of the same magnitude. This holds for the analysis of both quantiles and volatilities. The most liquid currencies in our sample also tend to be more integrated with the rest of the system, rarely displaying a number above 50% along their main diagonal, with the exceptions of JPY and CHF in the depreciation tails. In the case of these last two currencies, an interesting finding is highlighted by comparing the two tables: in terms of volatility spillovers, the amount of variation explained by their own shocks is below

[37] http://financialconnectedness.org/FX.html.

[38] 7% is approximately the 90th percentile in both the volatility- and VaR spillover tables.

50%, but this decreases for the left tail VaRs. This means that these currencies tend to receive fewer shocks from the market on the depreciation tail than they do in their volatility. Moreover, due to the symmetric nature of volatility, this might also signal that they are more prone to receive shocks on the right tail (appreciation) than they are on the left. This behavior is expected, because as *haven* currencies, the central banks in these countries are generally more concerned about episodes of strong appreciation than they are about depreciations, given that they are more sensitive on the appreciation tail of their distributions.

The Euro provides us with a notorious example of asymmetry when we compare the linkages in the left tail of the distribution with those involving volatility. While in the latter case the Euro transmits shocks above 7.0% on the markets of Switzerland (14%), Norway (8%) and Sweden (10%), in the left tail, the shocks transmitted by the Euro on these three markets are considerably smaller in magnitude, and only above 7.0% in the cases of Sweden (9%) and Norway (7%). Note that this should not necessarily be the case because by construction the FEVDs are normalized; thus, they are directly comparable in volatilities and quantiles. What it provides evidence of is the asymmetric nature of the propagation of shocks.

Figure 5.2 complements the analysis by showing the sums of the rows and columns presented in Tables 5.3 and 5.4. That is, it shows the total spillovers from each market to the rest of the system, and from the rest of the system to each market, in volatility (Panel A) and depreciation-VaR (Panel B). It is now readily apparent that the most vulnerable currencies in terms of volatility (let's say with above 70% of their shocks being explained by other markets) are the Euro, and the two Nordic currencies in the sample (NOK, SEK). These markets are also highly prone to receiving shocks in the depreciation tail, but other markets are also above the 70% threshold here, including GBP, AUD, and NZD.

Table 5.3. Volatility spillovers between the most traded free-floating currencies in the exchange rate market. The market that transmits the shock is shown in the columns, while the market that receives it is shown in the rows. Our sample runs from December 17, 2003 to September 5, 2016. The forecasting horizon was set at 10 days, and we used two lags in the case of volatility and one lag in the case of quantiles (following the BIC criterion)

	EUR	JPY	GBP	AUD	CAD	CHF	SEK	MXN	NZD	SGD	NOK	KRW	TRY	INR	BRL	ZAR	PLN	THB	COP	PHP	All to i
EUR	18.8	2.0	5.0	4.9	3.5	10.6	9.3	3.0	3.9	0.5	8.8	1.7	5.8	0.1	2.7	2.5	15.0	0.9	0.7	0.3	**81.2**
JPY	2.7	43.7	3.6	5.8	2.0	2.5	1.6	3.6	5.3	0.8	1.9	4.4	8.3	0.6	1.7	2.7	4.4	2.1	1.2	1.0	**56.3**
GBP	5.9	3.0	35.1	6.1	4.2	3.4	4.3	3.2	5.3	0.8	5.2	3.1	4.5	0.1	1.7	4.1	7.4	0.8	1.3	0.3	**64.9**
AUD	2.5	2.1	2.5	28.3	6.8	1.4	2.8	5.1	12.1	0.9	3.2	3.9	7.9	0.8	4.4	4.5	5.4	1.9	2.2	1.3	**71.7**
CAD	1.9	1.0	2.3	8.6	40.4	1.2	2.4	5.7	5.1	0.6	2.9	3.1	6.7	0.2	3.9	3.5	4.3	1.6	3.3	1.2	**59.6**
CHF	14.0	3.1	4.0	3.6	2.7	36.6	6.3	1.8	3.2	0.2	6.5	1.4	3.3	0.0	1.4	1.4	9.3	0.7	0.3	0.0	**63.4**
SEK	10.0	1.7	3.7	6.0	4.2	5.1	20.3	3.9	4.0	0.6	9.7	1.9	7.2	0.1	3.3	3.2	13.1	0.8	0.6	0.5	**79.7**
MXN	1.0	0.7	0.9	3.2	2.5	0.6	1.2	51.8	2.1	0.6	1.2	2.3	10.0	0.8	8.0	4.2	4.7	1.2	2.7	0.4	**48.2**
NZD	2.3	2.2	2.7	15.1	4.5	1.3	2.5	4.5	30.2	0.8	2.9	3.3	8.1	0.2	4.6	3.9	5.4	1.9	2.3	1.3	**69.8**
SGD	1.3	0.8	0.9	3.7	1.1	1.1	0.7	3.6	2.4	53.1	1.3	8.3	3.4	2.4	1.6	1.2	3.3	5.9	1.6	2.0	**46.9**
NOK	8.0	1.5	4.0	6.5	4.4	4.4	8.9	3.7	4.3	1.0	24.3	2.3	6.2	0.3	3.6	3.2	10.3	1.2	1.1	0.5	**75.7**
KRW	0.9	1.2	1.0	3.5	2.0	0.4	0.9	2.5	2.0	2.8	1.6	58.7	4.7	2.0	3.6	1.6	3.4	3.3	1.7	2.1	**41.3**
TRY	0.8	0.7	0.6	3.0	1.9	0.6	1.1	4.4	1.7	0.5	1.1	1.7	66.8	0.6	3.6	3.7	3.0	1.5	1.8	1.0	**33.2**
INR	0.1	0.5	0.1	0.9	0.2	0.1	0.2	1.5	0.6	1.1	0.1	1.3	1.0	86.5	1.0	0.4	0.6	1.5	0.9	1.4	**13.5**
BRL	0.5	0.9	0.3	2.7	1.9	0.3	0.6	6.5	2.1	0.4	0.5	3.2	8.5	0.4	63.1	2.0	1.4	1.0	3.3	0.5	**36.9**
ZAR	1.7	1.5	1.7	6.4	3.3	1.2	2.0	8.8	4.1	0.5	1.7	2.7	14.4	0.1	4.9	34.9	5.4	1.9	1.7	1.0	**65.1**
PLN	6.6	1.0	3.0	4.5	2.8	3.6	5.0	5.4	3.6	0.6	4.2	2.4	9.0	0.4	2.8	3.5	38.2	1.4	0.9	0.9	**61.8**
THB	0.3	0.2	0.3	1.2	0.7	0.2	0.3	0.5	0.9	0.9	0.7	1.7	0.8	1.2	0.2	0.6	1.2	85.8	0.6	1.7	**14.2**
COP	0.2	0.4	0.4	0.7	1.7	0.2	0.2	1.7	1.1	0.8	0.2	1.6	3.3	1.2	3.7	0.6	0.7	1.0	79.8	0.4	**20.2**
PHP	0.3	0.3	0.3	2.1	1.6	0.1	0.4	1.4	1.5	1.3	0.5	4.3	4.9	2.6	1.2	0.7	1.4	5.6	1.2	68.3	**31.7**
Total	**79.7**	**68.7**	**72.6**	**116.9**	**92.7**	**74.9**	**71.0**	**122.9**	**95.5**	**68.9**	**78.3**	**113.3**	**184.8**	**100.6**	**121.3**	**82.5**	**138.1**	**122.1**	**109.2**	**86.0**	
i to all	**60.9**	**25.0**	**37.5**	**88.6**	**52.3**	**38.2**	**50.7**	**71.1**	**65.3**	**15.8**	**54.1**	**54.6**	**118.0**	**14.1**	**58.2**	**47.6**	**99.9**	**36.3**	**29.4**	**17.7**	**51.8**

Table 5.4. VaR spillovers between the most traded free-floating currencies in the exchange rate market. The market that transmits the shock is shown in the columns, while the market that receives it is shown in the rows. Our sample runs from December 17, 2003 to September 5, 2016. The forecasting horizon was set at 10 days, and we used two lags in the case of volatility and one lag in the case of quantiles (following the BIC criterion).

	EUR	**JPY**	**GBP**	**AUD**	**CAD**	**CHF**	**SEK**	**MXN**	**NZD**	**SGD**	**NOK**	**KRW**	**TRY**	**INR**	**BRL**	**ZAR**	**PLN**	**THB**	**COP**	**PHP**	**All to i**
EUR	17.6	1.2	4.5	5.4	3.2	2.5	9.5	3.1	3.4	2.4	9.2	2.5	6.1	0.3	3.0	4.6	19.6	0.6	1.0	0.4	**82.4**
JPY	1.0	56.0	2.6	4.8	2.1	3.0	0.9	3.5	4.0	0.7	1.5	4.0	3.6	0.9	1.8	2.9	2.1	1.7	1.7	1.2	**44.0**
GBP	5.4	2.9	28.9	7.0	4.2	0.9	4.3	3.5	5.0	2.6	5.3	4.4	4.9	0.5	1.8	6.5	9.2	0.6	1.6	0.4	**71.1**
AUD	2.2	2.0	2.1	24.6	5.0	0.2	2.7	5.5	9.5	2.8	3.1	5.2	9.2	1.6	4.8	7.4	6.9	1.2	2.6	1.4	**75.4**
CAD	1.6	1.3	2.1	8.8	34.9	0.6	2.2	6.4	4.8	1.7	3.1	4.2	5.8	0.3	4.4	5.7	5.4	1.5	3.9	1.2	**65.1**
CHF	6.6	9.5	1.8	0.5	2.0	67.3	1.7	0.9	1.3	0.0	4.1	0.1	0.0	0.2	0.6	0.1	2.3	0.8	0.1	0.0	**32.7**
SEK	9.0	1.3	3.3	6.7	3.6	0.8	16.4	4.8	3.3	2.4	9.2	3.2	8.2	0.6	3.4	5.6	16.3	0.5	1.1	0.6	**83.6**
MXN	1.0	1.0	0.8	4.7	2.4	0.2	1.6	39.6	2.3	1.9	1.6	3.4	10.8	1.3	8.0	7.9	6.1	1.0	3.9	0.6	**60.4**
NZD	2.3	2.2	2.3	14.9	3.9	0.2	2.6	4.8	23.5	2.6	3.0	4.7	8.6	0.9	4.6	6.7	6.9	1.4	2.6	1.4	**76.5**
SGD	1.7	0.7	1.3	5.0	1.5	0.2	1.4	4.1	2.9	38.8	1.9	11.1	5.0	3.6	2.7	3.5	6.0	4.3	2.1	1.9	**61.2**
NOK	7.0	1.4	3.6	6.7	4.1	1.3	7.9	4.4	3.8	2.5	22.0	3.1	6.2	0.9	4.2	5.5	12.0	0.9	1.7	0.7	**78.0**
KRW	1.0	0.9	1.0	4.7	1.7	0.0	1.4	2.9	2.1	6.2	1.8	45.7	8.1	4.1	2.9	3.6	5.2	2.0	2.4	2.1	**54.3**
TRY	1.0	0.7	0.7	4.4	1.5	0.1	1.6	5.7	2.0	2.2	1.5	4.4	50.8	1.3	4.4	7.4	5.7	0.8	2.7	1.3	**49.2**
INR	0.2	0.7	0.2	2.0	0.2	0.0	0.5	2.1	1.0	2.6	0.4	3.6	3.3	73.2	2.0	1.7	1.7	1.4	1.6	1.6	**26.8**
BRL	0.5	1.1	0.3	3.8	2.0	0.0	0.8	7.2	2.2	1.5	0.7	3.9	9.0	1.2	52.4	4.7	2.4	0.9	4.6	0.7	**47.6**
ZAR	1.4	1.2	1.5	6.9	2.8	0.2	2.0	8.0	3.3	2.2	1.7	4.0	13.1	0.6	5.4	34.5	6.3	1.3	2.7	0.8	**65.5**
PLN	5.9	0.5	2.4	5.1	2.5	0.5	5.1	5.8	2.9	2.5	4.1	3.8	9.3	1.2	3.3	6.2	35.7	0.9	1.3	1.0	**64.3**
THB	0.2	0.2	0.3	1.1	0.7	0.1	0.2	0.6	0.9	1.6	0.6	1.5	0.3	1.4	0.3	0.7	1.1	86.0	0.6	1.5	**14.0**
COP	0.2	0.4	0.4	1.0	1.5	0.0	0.4	3.0	0.9	1.7	0.4	2.9	4.5	1.6	3.7	2.1	1.3	0.9	72.3	0.6	**27.7**
PHP	0.4	0.3	0.4	2.7	1.6	0.0	0.6	1.6	1.7	3.0	0.7	6.1	4.0	4.2	1.9	2.0	2.5	5.9	1.9	58.5	**41.5**
Total	**66.5**	**85.5**	**60.4**	**120.8**	**81.2**	**78.2**	**63.8**	**117.8**	**80.7**	**82.0**	**75.8**	**122.0**	**170.9**	**99.7**	**115.6**	**119.4**	**154.9**	**114.6**	**112.2**	**78.1**	
i to all	**48.8**	**29.5**	**31.5**	**96.2**	**46.3**	**10.8**	**47.4**	**78.1**	**57.2**	**43.2**	**53.9**	**76.2**	**120.1**	**26.6**	**63.2**	**84.8**	**119.2**	**28.6**	**39.9**	**19.6**	**56.1**

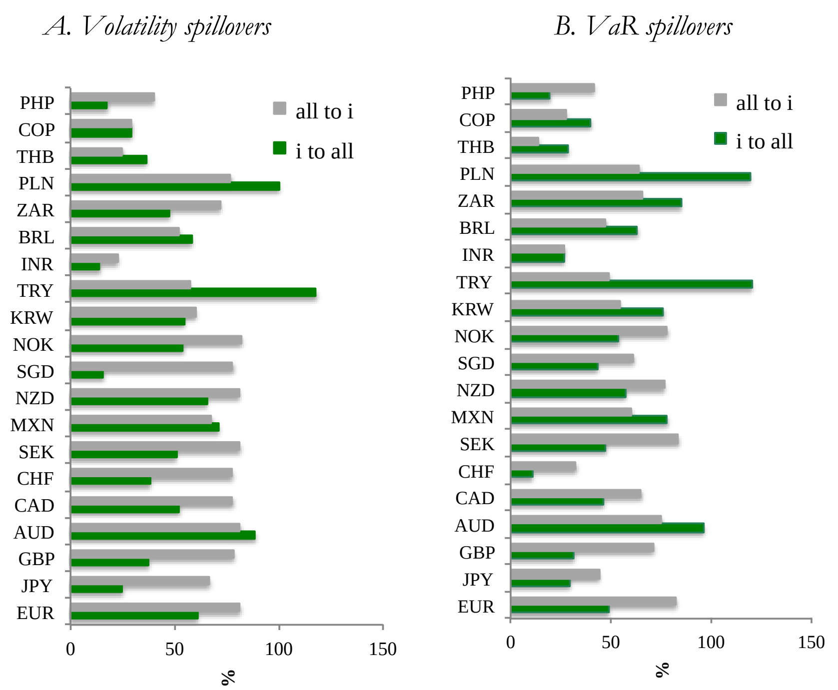


Figure 5.2. Total spillovers (static) during the sample period. The figure shows the sum of the rows and columns in Tables 5.3 and 5.4. That is, it shows the total spillovers from each market to the rest of the markets, and from the rest of the markets to each market, in volatility (Panel A) and depreciation-VaR (Panel B). The estimation sample runs from January 1, 2003 to September 5, 2016.

Yet, a comparison of the two figures does not allow us to establish whether, in general, the shocks propagate more in the left tail or in the volatilities, given that for some markets volatility shocks dominate, while for others quantile shocks dominate. Important asymmetries are found, for example, in the markets of South Africa, India, and South Korea. All these markets change from net-transmitters of volatility to net-receivers of shocks in the left tail. Once again this points to the asymmetric nature of their reactions to international FX spillovers. In general, after comparing Panels A and B in Figure 5.2, the analysis of JPY and CHF conducted above is confirmed.

B. Total volatility and VaR spillover indices

The static analysis reveals some interesting results but it is based on fixed parameters and, therefore, is not helpful in understanding how spillovers change over time. In order to assess the time-varying nature of spillovers, we estimate the model using a 250-day rolling window and a 10-day predictive horizon for the underlying variance decomposition[39]. Figure 5.3 shows the total volatility and quantile indices from December 17, 2003 to September 5, 2016.

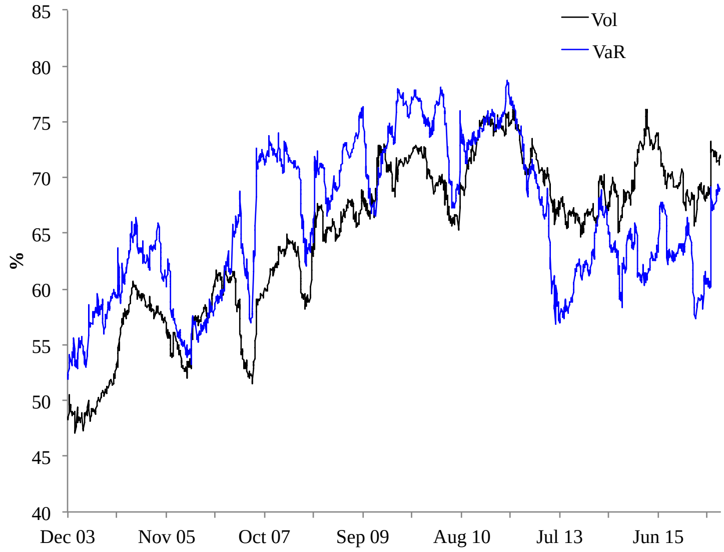


Figure 5.3: Total Volatility and VaR spillover indices. The figure shows the total (dynamic) indices based on volatility- and VaR-statistics for the full sample, which runs from December 17, 2003 to September 5, 2016 (the first observations were lost in the estimation process). The estimations were performed using rolling windows of 250 observations, forecasting horizon of 10 days, and two lags in the case of volatility and one lag in the case of VaR-statistics (following the BIC criterion). The VaR were constructed using an asymmetric CAViaR model that allows the two tails of the FX distribution to be treated differently.

The two systemic measures tend to co-move during the sample period, showing an increasing trend until 2012. However, while the volatility spillover index is lower than the quantile spillover index until 2012, this situation is reversed from 2012 onwards, coinciding with a huge reduction in quantile spillovers. Interestingly this reduction coincides with a reduction in the volume traded in FX markets[40]. It seems that extreme cross-market shocks are positively related to the total market turnover. This is important because, as shown by Mancini et al. (2013), liquidity in the foreign exchange market is not as stable as previously thought and it can foster financial crises in other markets of significant magnitudes.

[39] Our main results are not sensitive to realistic changes in the window length and the forecasting horizon. We adhered to the most frequent settings in the extant literature; see for example Greenwood-Nimmo et al. (2016).

[40] Daily FX market volumes fell from 5.4 to 5.1 trillion dollars between 2013 and 2016. Prior to 2013, the FX market witnessed an unstoppable year-on-year increment, accumulating an increment of 61% between 2007 and 2013

Meteor showers (cross-spillovers) were more important during the subprime crisis and its aftermath than during the rest of the sample, this finding only being evident when we focus on the quantile index. This means the volatility spillover index underestimated the impact of cross-spillovers by as many as 1,000 basis points (bp) in the year following the subprime crisis (July 2007 – August 2008) and by almost 500 bp during the European debt crisis in 2010. Since then the volatility spillover index has consistently overestimated the effect of meteor showers on the global FX market.

Furthermore, the quantile-based index seems more sensitive than the volatility-based index to events that impacted global currency markets, including the escalation in the Russian and Ukrainian conflict in 2014, the Greek referendum in June 2015, and Brexit in June 2016. The reduction of risk shown by the quantile-based index is also consistent with the recovery experienced by the US economy towards the end of the sample. The demand for US dollars and the lower demand for foreign currencies may explain the reduction in cross-spillovers between commodities and emerging market currencies during the period 2012-2016.

C. *Network analysis of two dates: subprime and Brexit*

Next we analyze some of the asymmetries in the propagation of shocks which can be observed when comparing net-spillovers on specific dates that were important for the FX market in terms of financial stability. In Figure 5.4, we plot the indices' dynamics before and after two major events in the global currency markets. Panel A shows both measures in the period around the subprime crisis – from August 1 to August 31, 2007[41], and Panel B shows the measures before and after the Brexit vote, held on June 23, 2016. Both were largely unexpected events with significant consequences for carry trade strategies and for the strength of the British Pound and other currencies, respectively. As can be observed, before August 16 the two systemic-currency indices, based on volatility and on left-tail-VaR statistics, displayed similar dynamics. Cross-spillovers accounted for around 53% of the total variation in the exchange rate markets according to the volatility index, and around 63% according to the VaR index. After August 16, the date identified by Melvin and Taylor (2009) as marking the onset of the crisis in the FX market, cross-spillovers rose to 59.12%, according to the volatility index, and remained at this level over the following days, while the increment was of 963 bp from 63 to 72.63%, according to the VaR index. The Brexit vote provides another significant example. While the volatility index (which was roughly 1,000 bp above the VaR-index during this episode) increased from 69.32% on June 24 to 72.82% on June 28 (350 bp), between the same dates the VaR index

[41] Melvin and Taylor (2009) pin the origin of the FX crisis to August 16, 2007, when a major unwinding of carry trade occurred and many currency investors suffered huge losses.

increased from 60.10% to 68.63% and remained at this level thereafter (that is, 853 bp above its initial magnitude).

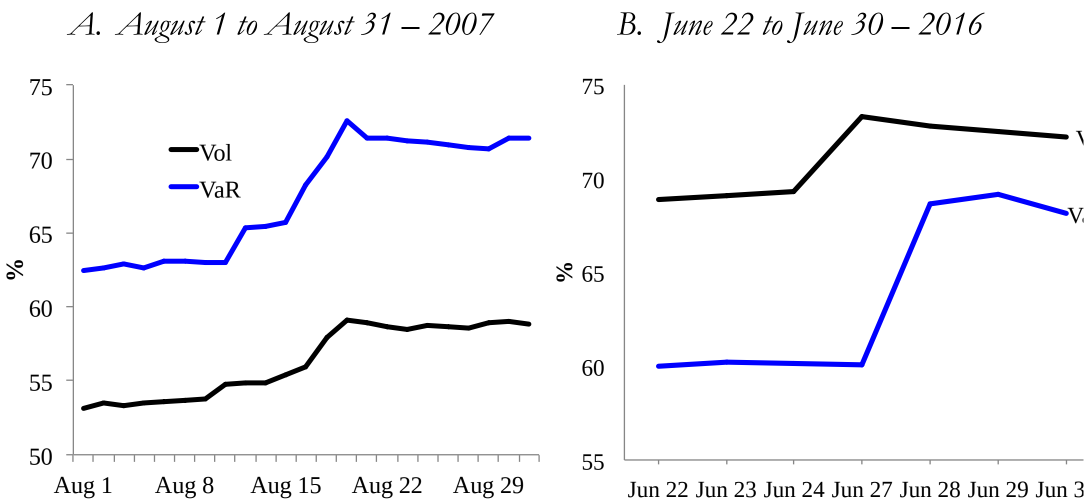
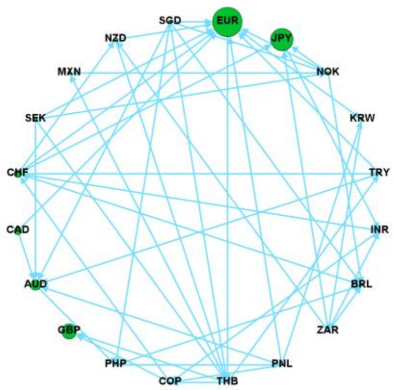


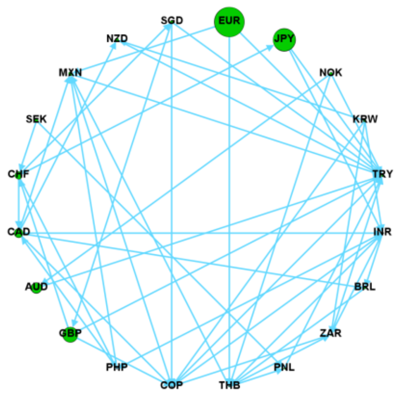
Figure 5.4: Total Volatility and VaR spillovers on two dates. The figure shows the two indices, based on volatility- and depreciation-VaR, during two turbulent episodes faced by the exchange rate market: the aftermath of the subprime crisis and the days immediately before and after the Brexit vote. The two statistics display different sensitiveness to these events. The plot was constructed after estimating volatility and VaRs using 20 series of the most traded floating currencies in our sample.

These significant differences have a critical impact on financial stability and need to be taken into consideration when conducting exercises that seek to monitor financial fragility around the world and when designing enhanced hedging mechanisms for international investors.

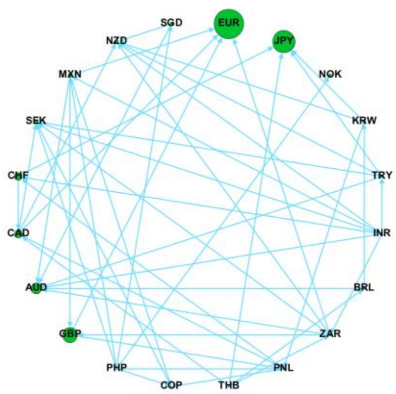
Figure 5.5 shows the graphical network representation of the volatility and quantile spillovers for the two periods analyzed above. The nodes represent each currency pair and their respective sizes are given by the turnover of each market, while the direction of the edges is given by the sign of the net pairwise spillover. We have plotted two dates: August 20, 2007, at the beginning of the global financial crisis and June 28, 2016, just after the Brexit vote. For the sake of clarity, we have only plotted the highest spillovers (above the 75th percentile) for each date.



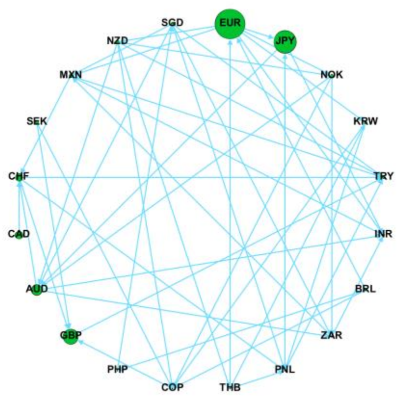
(a) 20 August 2007: net-volatility spillovers



(b) 20 August 2007: net-quantile spillovers



(c) 28 June 2016: net-volatility spillovers



(d) 28 June 2016: net-quantile spillovers

Figure 5.5: Net volatility and quantile spillovers on selected dates. The figure shows the net-volatility (left) and depreciation (right) spillovers among the 20 markets in our sample for two selected dates August 20, 2007 (subprime FX crash) and June 28, 2016 (Brexit). We only plot the highest 25% spillovers for each date. The size of each node is given by the turnover of each market in 2016.

Panel (a) presents the pairwise spillovers in volatilities for August 20, 2007. It shows that the Euro, Yen, Swiss Franc, and to a lesser extent other liquid currencies such as the Australian Dollar, were the main receivers of shocks. In contrast, if we focus on panel (b), which shows the net pairwise spillovers across quantiles, it is Turkey and the other emerging markets that received most of the shocks. We believe that these outcomes reflect the fact that the subprime crisis led to massive flows of capital and the reallocation of carry-trade portfolios, which experienced considerable losses. This process primarily affected strong currencies, such as the Euro and Yen, in the right tail of their distributions (appreciations), but it also affected weaker currencies, such as the Turkish Lira, in their left tails. In terms of financial stability, it is necessary to understand these phenomena and to monitor not only the appreciation pressures of strong currencies, but also (and we would add mainly) the depreciation pressures faced by weaker currencies, which all told are more likely to have to face currency crises.

A similar analysis can be conducted in the wake of the Brexit vote. Clearly, the net receivers of volatility shocks were the commodity currencies and strong currencies, in other words the currencies associated with more developed markets. Nevertheless, panel (d) shows that other currencies, including the South African Rand, the Turkish Lira and the Indian Rupiah, were also affected in the left tail of their distributions. Naturally, some currencies, including the Euro and Swiss Franc, were affected regardless of the measure, because the quantiles are not independent of the variances. Surprisingly, the British Pound only received *net*-shocks in volatility from Poland and Mexico, and in the quantiles from Switzerland, Sweden and Colombia. The impact recorded by the currencies of the eastern European countries is as expected, given that they are directly affected by the variations suffered by the Euro market.

D. D. Turnover, liquidity and spillovers

Finally, we are also interested in analyzing how traded volume helps us understand the patterns of global volatility and VaR spillovers in the FX market. Figure 5.6 shows the net-volatility spillovers among the quartiles of the currencies in our sample, sorted according to traded volume in 2016[42]. The analysis runs from December 17, 2003 to September 5, 2016. The first quartile corresponds to the most traded currencies, while the last quartile groups the least traded currencies. The traded volume is as reported in the Bank of International Settlements (2016). The group in the column is the one that transmits the shock while the group in t he row is the one that receives it.

Our intuition based on the literature on exchange rate fundamentals rooted in market microstructures, as in Evans (2011), is that, rather than macro-fundamentals, liquidity matters for spillovers. Thus, world currency spillovers should behave differently according to how much investors trade them. Indeed, we are able to document that this is in fact the case. In general, if we divide our sample into three periods – corresponding roughly to US dollar depreciation (from January 2003 to June 2008), market turbulence without any clear trend in the US dollar series (from July 2008 to May 2012), and US dollar appreciation (from June 2012 to September 2016, when our sample ends)[43] – we can document several trends. As far as volatility spillovers are concerned (Figure 5.6), the least traded currencies (those in quartile 4) are almost always net-receivers of volatility shocks and, when they are transmitters, the net

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[42]Individual net volatility and VaR spillover measures are provided in Figures 5.8 and 5.9 of the appendix.

[43] See Figure 5.2.

spillover is low. If we examine the currencies in quartiles 1, 2 and 3, we see that during the period of dollar depreciation there was no clear trend in the direction of net spillovers, but that they were relatively low. During turbulent times, the more liquid a currency was the more shocks it received from less liquid currencies. This behavior was reversed during the period of US dollar appreciation, when the more liquid a currency was the more shocks it transmitted to the rest of the markets.

Interestingly, the shocks propagate as in *a cascade*: the more liquid a set of currencies is the more likely *it affects* all the other currencies, *during depreciation periods* (against the USD). Conversely, the more liquid it is the more likely *it gets affected* by all the other currencies *during turbulent periods that lack a clear trend* in terms of appreciation or depreciation.

The situation is very different when we examine tail spillovers (Figure 5.7). Currencies in quartiles 1 and 2 (the most liquid) are, by rule, net-receivers, while those in quartiles 3 and 4 (the least liquid) are net-transmitters. This is very likely a consequence of the latter being considerably more exposed to downside risk in the global currency markets. Notice, in any case, that this is a net result and as such it is mute above the size of the shocks.

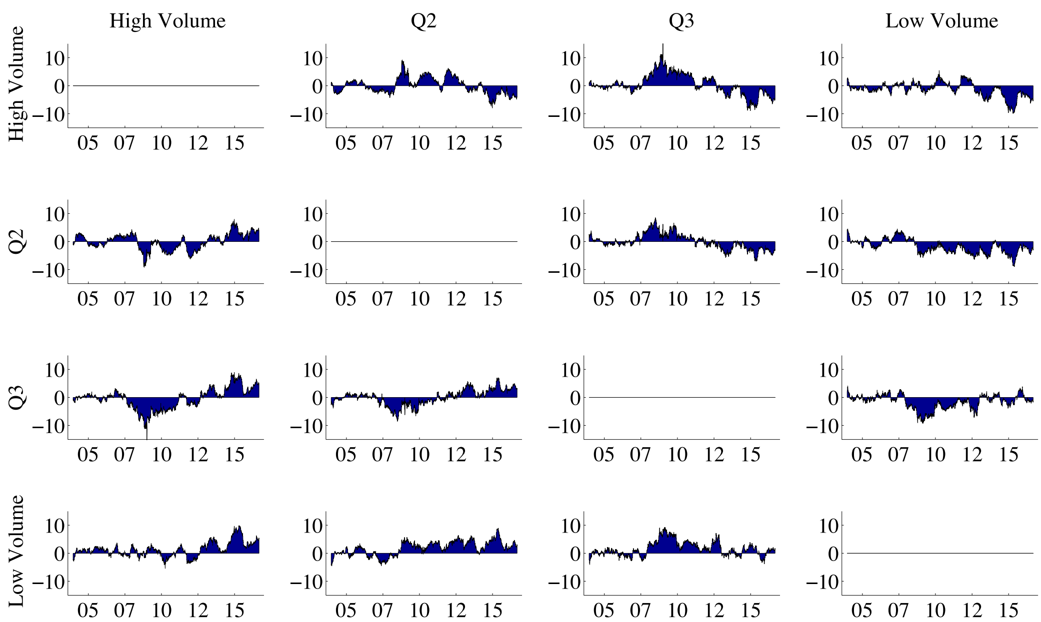


Figure 5.6: Net volatility spillovers among world currencies sorted according to traded volume. The figure shows net-volatility spillovers among the quartiles of the currencies in our sample, sorted according to traded volume in 2016. The first quartile corresponds to the most traded currencies, while the last quartile groups the least traded currencies. The traded volume is as reported in the Bank of International Settlements Triennial Report (BIS, 2016). The group in the column is the one that transmits the shock

while the group in the row is the one that receives it. The estimations were performed using rolling windows of 250 observations and a forecasting horizon of 10 days.

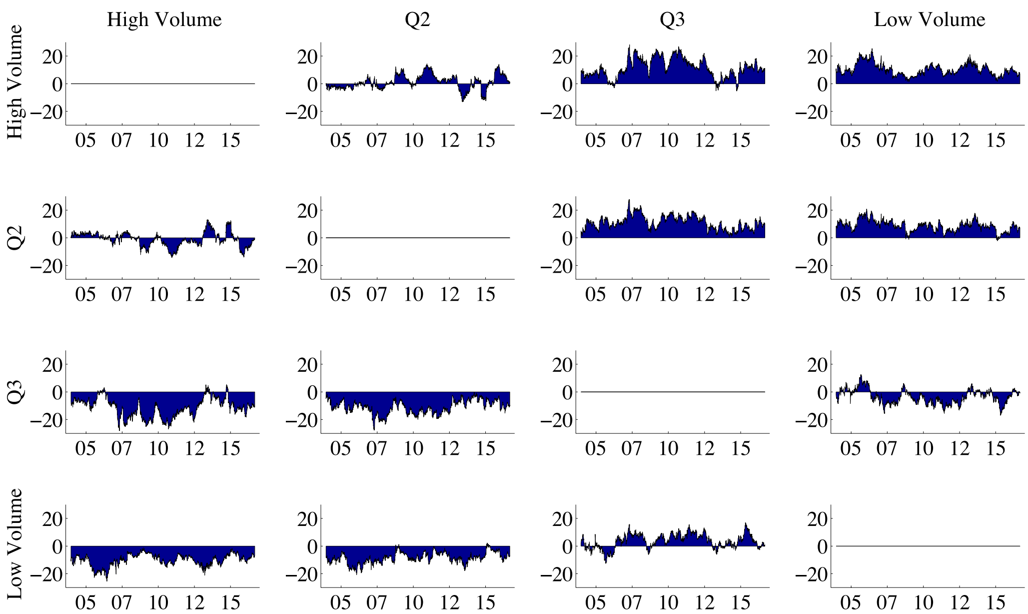


Figure 5.7: Net VaR spillovers among world currencies sorted according to traded volume. The figure shows the net-VaR spillovers among the quartiles of the currencies in our sample, sorted according to traded-volume in 2016. The first quartile corresponds to the most traded currencies, while the last quartile groups the least traded currencies. The traded volume is as reported in the Bank of International Settlements Triennial Report (BIS, 2016). The group in the column is the one that transmits the shock while the group in the row is the one that receives it. The estimations were performed using rolling windows of 250 observations and a forecasting horizon of 10 days. The VaR were constructed using an asymmetric CAViaR model that allows the two tails in the distribution to be treated differently.

5.5. Conclusions

We estimate spillovers between volatilities and between downside risk VaRs (associated with depreciations) for 20 currencies of both mature and emerging FX markets. Our depreciation tail measure was constructed using a CAViaR model with asymmetric slopes that allows us to treat each tail of the daily variations in the FX market differently.

First, we find that risk measurement varies considerably depending on the part of the distribution targeted by the analysis. That is, the most vulnerable FX markets differ if we focus on the depreciation tail as opposed to on volatility. To document this, we analyzed recent events in the history of FX markets – specifically the subprime crash and the Brexit vote – by means of directional pairwise statistics and graphical networks.

Thus, we find that the least liquid currency markets tend to be more vulnerable and to transmit more shocks in the left tail of the distribution than is the case with volatility. This is fundamental for the correct assessment of systemic risk in currency markets and for monitoring financial fragility and distress in currency markets around the world. In keeping with this outcome, we construct an index of financial fragility based on cross-spillovers among the left tails of the distributions (depreciation episodes) and show that this index is much more sensitive than a traditional volatility index to such events as political upheavals and global crises.

Finally, for each currency in our sample, we employed turnover as a proxy for liquidity. This has helped us shed new light on the propagation mechanisms of currency shocks. We find that the most liquid currencies are generally net-transmitters of volatility during periods of US dollar appreciation, while the most liquid currencies are net-receivers of volatility in periods of turbulence lacking any clear trend. Similarly, the least liquid currencies almost always behave as net-receivers of volatility, rarely interacting with the rest of the systems, which shows their lack of integration in global financial markets.

In contrast, when we focus on tail spillovers corresponding to depreciation tails, the general perspective changes considerably. The most liquid currencies are almost always net-receivers of shocks, while those in the least liquid quartiles (3 and 4) are net-transmitters. This finding underlies the nature of the latter, which are considerably more exposed to downside risk in global currency markets than are the former. It also highlights the convenience of using a measure like the one proposed here, based on depreciation-quantiles, when assessing global financial stability conditions in FX markets.

Appendix to Chapter 5

Table A1. Summary statistics of the annualized volatility of the FX log-variations

The table shows summary statistics of FX volatility in annualized terms. The third and fourth moments of the series are presented for the logarithmic volatilities, which were used in the estimation of the spillover volatility indices. As expected, the series with the highest standard deviations and means are found in developing countries (i.e. South Africa, Brazil, and Colombia). In contrast, the lowest levels are found in developed countries (i.e. Europe and Japan).

	EUR	JPY	GBP	AUD	CAD	CHF	SEK	MXN	NZD	SGD
Mean	10.73	10.61	10.12	13.66	10.41	11.51	13.32	11.26	14.90	5.81
Median	9.57	9.26	8.83	11.64	9.26	10.30	11.61	9.34	13.11	5.07
Maximum	52.93	86.29	145.60	124.69	68.25	227.90	87.92	203.75	100.69	33.58
Minimum	0.00	0.42	0.00	1.53	1.27	0.00	1.82	0.00	2.19	0.33
Std. Dev.	5.58	6.33	6.06	8.66	5.65	7.11	7.25	9.05	8.12	3.10
Skewness	-0.13	-0.02	0.15	0.35	0.02	0.02	0.26	0.04	0.26	0.10
Kurtosis	3.50	3.89	3.86	3.91	3.31	4.02	3.17	4.43	3.59	3.96
	NOK	KRW	TRY	INR	BRL	ZAR	PLN	THB	COP	PHP
Mean	13.81	9.43	13.58	6.36	15.98	19.82	15.63	6.75	10.76	5.80
Median	12.24	7.39	11.20	5.46	13.62	17.03	13.41	5.08	8.19	5.32
Maximum	84.92	164.88	90.23	60.87	131.59	193.68	95.92	83.92	232.30	30.94
Minimum	2.06	0.00	0.00	0.00	0.00	1.48	0.45	0.00	0.00	0.00
Std. Dev.	7.31	9.03	9.14	5.28	10.47	11.28	9.27	6.04	9.97	3.65
Skewness	0.17	-0.35	-0.01	-0.77	-1.11	0.27	0.07	0.23	-0.89	-0.93
Kurtosis	3.23	4.49	4.63	3.76	7.24	3.89	3.70	4.09	5.09	4.36

Table A2. CAViaR estimation results

The table shows the regression results after fitting a CAViaR model at 95% level of confidence with asymmetric slopes, to each FX series. The following equation was employed in each case.

$$q_t = \beta_0 + \beta_1 q_{t-i} + \beta_2 y_{t-1}{}^{-} + \beta_3 y_{t-1}{}^{+}$$

Negative and positive shocks are seen to have a different effect on the depreciation tail, which supports the use of an asymmetric-slope approach.

Currency	β_0	β_1	β_2	β_3
EUR	0.01	0.97	0.09	0.00
JPY	0.03	0.91	0.08	-0.15
GBP	0.01	0.95	0.12	-0.07
AUD	0.03	0.92	0.19	-0.08
CAD	0.01	0.92	0.17	-0.12
CHF	0.01	0.96	0.04	-0.09
SEK	0.02	0.95	0.10	-0.04
MXN	0.02	0.91	0.24	-0.10
NZD	0.02	0.93	0.16	-0.08
SGD	0.01	0.91	0.19	-0.10
NOK	0.02	0.93	0.13	-0.08
KRW	0.02	0.93	0.23	0.03
TRY	0.06	0.84	0.39	-0.15
INR	0.01	0.89	0.32	-0.14
BRL	0.04	0.88	0.28	-0.14
ZAR	0.05	0.90	0.22	-0.07
PLN	0.02	0.91	0.24	-0.09
THB	0.01	0.87	0.27	-0.22
COP	0.03	0.87	0.30	-0.14
PHP	0.03	0.88	0.20	-0.14
Mean	0.02	0.91	0.20	-0.10
Median	0.02	0.91	0.20	-0.09
Maximum	0.06	0.97	0.39	0.03
Minimum	0.01	0.84	0.04	-0.22
Std. Dev.	0.02	0.03	0.09	0.06
Skewness	1.12	-0.18	0.18	0.32
Kurtosis	3.62	2.56	2.48	3.41

Table A3. Estimated VaR summary statistics

The summary statistics were calculated from the VaR estimated after fitting a CAViaR model with asymmetric slopes. Commodity currencies, such as AUD, CAD, SEK, NZD, NOK, BRL, and ZAR, possess a higher risk than most of the other currencies. A second aspect that can be seen is that countries with capital control and with a history of foreign exchange interventions, such as INR, SGD and THB, have lower volatility.

	EUR	*JPY*	*GBP*	*AUD*	*CAD*	*CHF*	*SEK*	*MXN*	*NZD*	*SGD*
Mean	0.99	0.97	0.96	1.30	0.97	1.03	1.27	1.14	1.36	0.48
Median	0.96	0.93	0.90	1.19	0.89	0.98	1.19	1.03	1.27	0.45
Maximum	2.13	2.61	2.61	6.19	3.51	2.46	2.88	5.98	4.40	1.43
Minimum	0.47	0.50	0.40	0.66	0.41	0.47	0.77	0.44	0.69	0.22
Std. Dev.	0.29	0.26	0.34	0.55	0.36	0.28	0.36	0.54	0.44	0.15
Skewness	0.93	1.51	2.14	4.16	2.49	1.14	2.01	2.92	2.32	1.55
Kurtosis	4.40	7.43	9.43	28.88	13.47	5.55	7.59	17.90	11.86	7.19
	NOK	*KRW*	*TRY*	*INR*	*BRL*	*ZAR*	*PLN*	*THB*	*COP*	*PHP*
Mean	1.27	0.95	1.41	0.74	1.57	1.79	1.44	0.57	1.08	0.62
Median	1.20	0.80	1.26	0.67	1.40	1.66	1.28	0.49	0.91	0.59
Maximum	3.47	7.17	7.48	3.38	7.35	7.65	5.25	3.77	5.05	1.34
Minimum	0.65	0.32	0.58	0.08	0.55	0.93	0.52	0.17	0.30	0.30
Std. Dev.	0.35	0.68	0.63	0.40	0.74	0.59	0.63	0.35	0.57	0.16
Skewness	1.86	4.54	2.66	1.40	2.71	3.16	2.13	3.77	1.92	0.98
Kurtosis	8.91	30.91	14.98	6.77	15.56	21.59	9.39	22.55	9.25	4.20

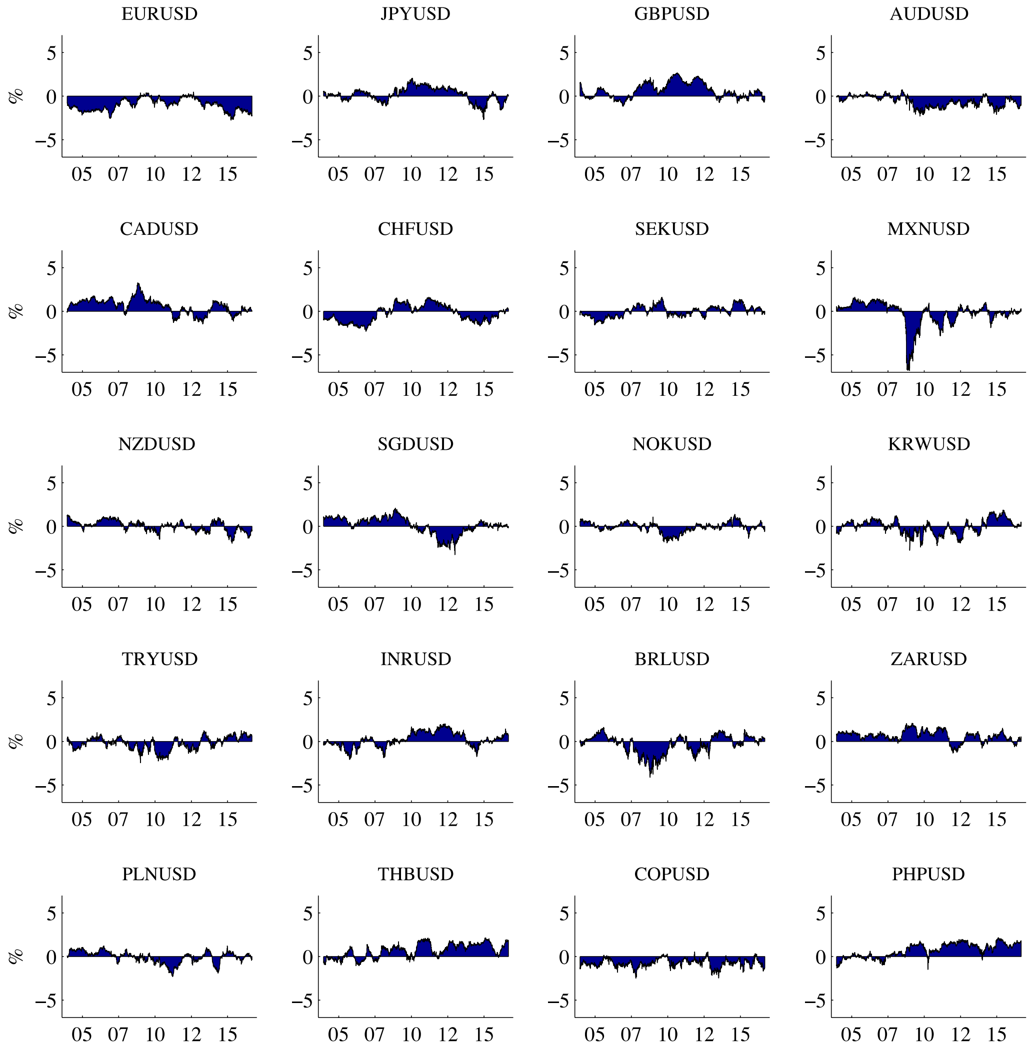


Figure 5.8: Net volatility spillovers from *all* markets to market *i*. The figure shows net-volatility spillovers from the rest of the markets to each market. A positive value indicates that the market is a net-receiver, while a negative sign indicates that it is a net-transmitter of volatility on a certain date. The estimations were performed using rolling windows of 250 observations, a forecasting horizon of 10 days, and two lags in the case of volatility and one lag in the case of VaR-statistics. The VaR were constructed using an asymmetric CAViaR model

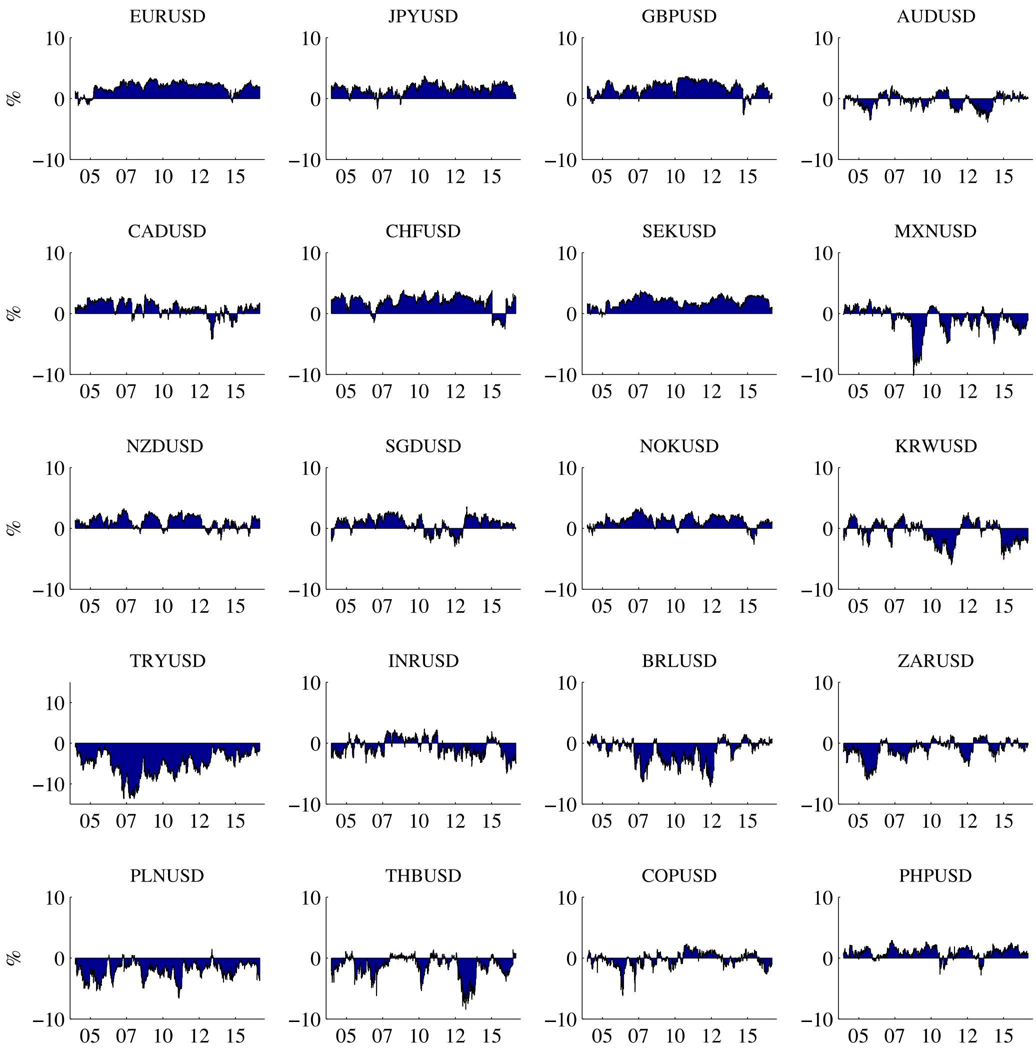


Figure 5.9: Net VaR spillovers from *all* markets to market *i*. The figure shows the net-value at risk spillovers from the rest of the markets to each market. A positive value indicates that the market is a net-receiver, while a negative sign indicates that it is a net-transmitter of volatility on a certain date. The estimations were performed using rolling windows of 250 observations, a forecasting horizon of 10 days, and two lags in the case of volatility and one lag in the case of VaR-statistics. The VaR were constructed using an asymmetric CAViaR model.

Chapter 6: Spillovers from the United States to Latin American and G7 Stock Markets: A VAR Quantile Analysis

Abstract

We estimate multivariate quantile models to measure the responses of the six main Latin American (LA) stock markets to a shock in the United States (US) stock index. We compare the regional responses with those of seven developed markets. In general, we document weaker tail-codependences between the US and LA than those between the US and the mature markets. Our results suggest possible diversification strategies that could be exploited by investing in Latin America following a sizable shock to the US market. We also document asymmetrical responses to the shocks depending on the conditioning quantile at which they are calculated.

6.1. Introduction

The analysis of spillovers between cross-national stock market returns is of increasing interest in the empirical finance literature. A better understanding of the phenomenon is important for practitioners and policy makers alike since it can provide a sound basis for designing portfolio allocation, market diversification and hedging strategies, at the same time as highlighting market scenarios under which an actively guided monetary or macroprudential policy is likely to achieve the best outcomes in terms of preserving financial stability, for instance, in seeking to avoid international financial contagion.

However, research in the field has overwhelmingly focused on evaluating the effects of shocks on the first two conditional moments of return distributions, while ignoring other parts of the distributions. In this strand of the literature, studies analyzing stock market return spillovers, interdependence and contagion abound, which means a complete summary of this work would be impracticable in the scope of this paper. To name just a few, Becker et al. (1995), Bekaert et al. (2005), Bekaert et al. (2009), Jayasuriya (2011), Ehrmann et al. (2011), Bekaert et al. (2014) study the spillovers between the means of the return distributions, while other authors analyze the conditional variance spillovers to the mean (Bae et al., 2007; Diebold and Yilmaz, 2009; Beirne et al., 2010), and the pure volatility spillovers (Arouri et al., 2011; Rittler, 2011; Neaime, 2012; Lee, 2013).

There are also many related studies that specifically test the existence of financial integration, market interdependence and contagion, considering Latin American markets, following a significant shock to global financial markets, especially from the US. Among this group we observe a first generation of studies that using linear models, most notably cointegrated vectors, document a strong relationship between the Brazilian, Mexican, Argentinian, Chilean, Colombian and Venezuelan markets and the US market, particularly during crises episodes. This results lead to suggest that potential diversification of risk trough investing in different Latin American markets is very limited from the perspective of an international investor (Chen et al., 2002; Fernández and Sosvilla, 2003; Pagan and Soydemir, 2000). Some authors have pointed out to the high trade of LA markets with the US, as a possible factor underlying such a strong relationship (Johnson and Soenen, 2003).

Nevertheless, some of the first-generation studies also documented a non-linear relation between Latin American markets and the US market, using structural break tests as in Fernández and Sosvilla (2003), partitions of the sample into sub-periods as in Chen et al. (2002) or even logistic regression and extreme value theory as in Bae et al. (2003). In the same vein, Chan-Lau et al. (2004), estimate bivariate extreme dependency measures, to quantify negative and positive equity returns contagion. They report a higher degree of integration between the LA markets and the US market, compared to the level of integration of East Asian markets and the US, and they document as well stronger 'bear' contagion than 'bull' contagion. That is, a greater probability of contagion following extreme negative than following extreme positive returns in a given market, particularly in the LA markets.

This apparent non-linearity of the relationship has been subsequently confirmed by Lahrech and Sylwester (2011). Those authors use dynamic conditional correlations, blended with smooth transition models, for testing the degree of market integration between LA markets and the US. They find that indeed the level of market integration increased from 1988 to 2004, for all the LA markets, but they also document an asymmetric behavior at this respect within the LA markets. For instance, while Argentina, Brazil and Mexico show a high correlation with the US market and experienced a substantial increment in their market correlations during the sample period, Chile still displays a more stable lower correlation with the US, becoming a possible diversification opportunity from the perspective of an international investor.

Other studies have clearly pointed out to other sources of non-linearity in the relationship between LA markets and the US market. For instance, Chiang and Zheng (2010) studied herd behavior in global stock markets. They report two key findings: first they identify the role of the US market in examining local market herding behavior (the evidence shows that in the majority of cases, investors in each national market are herding around the US market). Second, they find evidence of herding behavior occurring in developed markets and in Asian markets, but less supportive evidence for herding behavior in Latin

American markets. Moreover, herding behavior is clearly more apparent during crisis episodes than during regular times.

Given the literature above, the strategy of focusing solely in analyzing the transmission across the markets in the first two moment of the return distributions, and by means of linear models, does not appear completely justified on empirical grounds. Moreover there seems to be a strong temporal dependence between the quantiles of the univariate distributions of financial returns, and not only between their second moments (Engle and Manganelli, 2004; Baur et al., 2012). Thus, it seems plausible to forecast a fuller range of the distribution using contemporaneous information, and our attention need not be restricted solely to the first two moments.

Quantile regression models constitute a promising tool for obtaining a better understanding of the way in which financial spillovers occur and for quantifying the sensitivity of different markets to international shocks. These models are known to be robust to outliers, which is particularly important for analyzing financial time series. They are also semi-parametric in nature and, therefore, require minimal distributional assumptions on the underlying data generating process (DGP). Moreover, they offer greater flexibility for analyzing different market scenarios. For instance, while lower quantiles can be associated with bearish markets, higher quantiles are intuitively associated with bullish markets. Therefore, very high or very low quantiles can be expected to be related to other widely studied financial phenomena, such as bubbles, contagion or episodes of financial distress.

For the aforementioned reasons, it is not surprising, therefore, that quantile models have been incorporated into the financial literature. For instance, Basset and Chen (2001) use quantile regressions to study the way in which different portfolio styles (based on their sensitivity to certain market indexes) influence the whole distribution of the portfolios conditional returns, especially at the tail of this distribution. Engle and Manganelli (2004) use conditional quantile models to directly calculate Value at Risk statistics, instead of recovering them by estimating the conditional moments of a set of stock returns. Baur and Schulze (2005) analyze coexceedances in the markets, over specific thresholds, as they seek to identify episodes of financial contagion. Li and Miu (2010) employ a binary quantile model to examine predictions of bankruptcy employing market- and accounting-based factors.

More recently, Tsai (2012) documents a negative relationship between exchange rates and the stock price index in the highest and lowest quantiles of the distribution; however, the study does not provide evidence of a significant relationship between the variables in the quantiles near the median. Lee and Li (2012) document a non-linear diversification effect on firm performance, dependent on the quantile of the distribution. Ciner et al. (2013) use quantile regressions to explore whether the dependences between different asset classes in the US and the UK differ during episodes of extreme price movements. Gebka and Wohar (2013), using quantile regressions, document a strong non-linear causality in the highest and lowest quantiles of the series of volume and stock returns in the Pacific Basin countries. They also report a non-statistically significant relationship between volume and returns in the median of the distribution. Finally, Rubia and Sanchis-Marco (2013) analyze the predictability of different stock portfolios in the tails of the distribution, by using variables that proxy for market liquidity and trading conditions.

In common with any traditional regression, quantile models are susceptible to reverse causality, simultaneous equations, omitted variables, and, in general, to endogenous regressor considerations. Within the framework of cross-national spillovers, these concerns acquire particular relevance and so theoretical restrictions need to be identified before quantifying the relationship between markets in different quantiles of the returns distribution. Such restrictions can be very naturally imposed in the multivariate quantile setting proposed by White et al. (2015). Their framework can be thought of as a vector autoregressive (VAR) extension to quantile models, enabling the direct analysis of the degree of tail interdependence among different random variables.

In this paper we measure the response of the six main Latin American (LA) stock markets to a shock in the United States (US) stock index. We analyze the markets of Brazil, Chile, Mexico, Colombia, Argentina and Peru and we also report the results for six mature markets, for the sake of comparison (the United Kingdom, Germany, France, Canada, Italy and Japan). Unlike previous studies that make use of traditional quantile regressions to analyze dependence or spillovers between markets (Mensi et al., 2014)[44], we use the multivariate quantile model proposed by White at al. (2015). This model has an additional advantage over reduced form models that analyze dependence in a broader sense than the traditional regression framework, using, for example, copula functions (Aloui et al., 2011). Namely, it allows the direct tracing of structural shocks from the US to the other markets, through the estimation of different quantiles of the multivariate distribution of market returns and by imposing minimal theoretical restrictions on the multivariate DGP describing the data. By so doing, we are able to compute pseudo impulse-response functions (PIRFs) during different market scenarios, and to document facts about the persistence and dynamics of the system after facing a shock conditional on the quantiles of the returns distribution.

In short, this study contributes to studies of contagion, market integration and cross-border spillovers during both regular and crisis episodes by applying multivariate quantile analysis to solve traditional problems in finance. Most of the studies in this branch do not consider specific quantiles of the

[44] These authors study the impact of shocks on the BRICs' markets.

distributions and, therefore, they do not condition their results to specific market situations. Instead, they focus on the mean of the distributions, which could underestimate the real effects of an international shock. Even traditional quantile studies do not make any attempt to identify structural shocks by recourse to theory, nor are they able to analyze certain features of the shocks, such as their persistence, during different market scenarios.

We focus our analysis on Latin American stock markets, which have been characterized by a highly positive dynamic in recent decades, in terms of market capitalization and liquidity ratios, after a far-reaching process of market liberalization and reforms to pension funds across the continent during the 80s and 90s (Gill et al., 2005; De la Torre et al., 2007). Moreover, the global financial crisis between 2007 and 2010 appears to have fostered financial flows into LA markets, as capital investors looked for diversification opportunities outside the mature markets, and as liquidity began to flourish around the globe, following persistently low market interest rates in the major economies.

Thus, between 2005 and 2014, the combined domestic market capitalization, reported on the webpage of the World Federation of Exchanges, of the markets in Buenos Aires, Sao Paolo, Santiago, Bogota, Mexico City and Lima, rose by almost a hundred per cent, climbing from USD 972.50 billion to USD 1,843.11 billion, in less than ten years. The indicator peaked in 2010 at USD 2717.47 billion, when global financial conditions began to be regularized, primarily in the US. After 2010, a marked fall was recorded in the indicators of the regional markets, especially in the largest, that of Brazil, which represents around a half of the total. In all likelihood this can be attributed to flight-to-quality scenarios and disparate expectations among investors in terms of the future of the emerging markets' economic fundamentals, for instance, in relation to commodity exports[45].

The dynamics of these regional markets is of interest, especially for institutional investors around the globe who are constantly looking for opportunities to diversify their portfolios. Moreover, a shock originating in the US market is of considerable interest for the LA economies given that the US economy is the destination of around 40% of the region's total exports and imports, making it by far the main commercial partner of LA countries[46].

In general we documented smaller dependences between the LA markets and the US market than those between the US and the developed economies, especially in the highest and lowest quantiles. Nevertheless, we found an

[45] Among the markets in our sample the percentage of total market capitalization is: Brazil (38.3%), México (31.4%), Chile (14.9%), Colombia (6.7%), Peru (4.4%) and Argentina (4.4%). The market with the highest market capitalization (relative to GDP) is Chile (79.2%). http://data.worldbank.org/

[46] Data taken from the webpage of the *Comisión Económica para América Latina y el Caribe* (CEPAL).

asymmetrical response to the shocks originating in the US market, depending on the conditioning quantile analyzed. This result holds regardless of whether the market under consideration is mature or emerging, an outcome that can be attributed to the phenomenon of flight-to-quality operating in the lowest quantiles (a positive shock in the US is followed by a negative reaction in the other markets), and a situation of liquidity spillovers between the markets in the highest quantiles (a positive shock in the US is followed by a positive reaction in the other markets).

Another useful way to understand our results is to consider the unconditional stock return distributions without focusing on any specific quantiles. In this case, a shock to the US market can be expected to flatten the distribution of financial returns in all other markets. This increases the likelihood of observing extreme returns in these markets in the period following the original shock. In other words, a shock to the US market will increase the Value at Risk (VaR) statistics associated with the other markets. However, this change is not symmetrical in the tails. For some countries, the right tail of the returns increases more than the left tail; for others, the situation is reversed. These results have obvious implications in terms of the optimal implementation of hedging strategies, portfolio diversification, and risk management, but also with regards to the optimal design of monetary and macroprudential policies.

The rest of the paper is organized as follows. First, we present a brief introduction to quantile modeling and the specific multivariate multiquantile MVMQ (1,1) employed here. We then describe the data used to perform the estimations. The main results and discussion are presented in the next section. Finally, we outline the conclusions that can be drawn from this study.

6.2. Methodology

Since Koenker and Basset's (1978) seminal contribution, quantile models have been of growing interest in many fields of economics, being applied in disciplines that range from finance to macroeconomics and labor economics (Koenker, 2005). Quantile regression allows the researcher to study the relationship between economic variables not only at the center but also across the entire conditional distribution of the dependent variable. In traditional quantile regression, the quantiles of a dependent variable are assumed to be linearly dependent on a set of conditioning variables.

As in any structural modeling set up, causal relationships can only be identified after maintaining the exogeneity condition of the conditioning variables (Pearl, 2014; Heckman 2008). In a continuously integrating global financial market, this condition is difficult to assume in practice. Global investors can rapidly change their positions, by restructuring their portfolios. In turn, this has a feedback effect on global markets, breaking down the exogeneity requirement. Therefore, in order to recover the effects of specific structural innovations over a given system of financial prices, it is necessary to resort to the traditional multivariate time series tools, such as structural vector autoregressions (Sims, 1980), which have been available in the literature for decades.

Multivariate quantile models (MVMQ) allow the researcher to perform this task. They were recently proposed by White et al. (2015) as a multivariate extension of the influential CAViaR model developed by Engle and Maganelli (2004). The authors use an MVMQ (1,1) model to analyze the sensitivity of financial institutions to systemic shocks (a market index constructed as a common factor of financial institutions' returns). This allows them to construct a measure of the performance of each financial institution facing financial distress (with a specific focus on the low quantiles). The general idea behind MVMQ models is that the quantiles of the distribution of a time series r_t potentially depend on its own lags and on the lags of certain covariates of interest. Specifically, the MVMQ (1,1) model employed in this study is given by the following two equations:

$$q_{1t} = c_1(\theta) + a_{11}(\theta)|r_{1t-1}| + a_{12}(\theta)|r_{2t-1}| + b_{11}(\theta)q_{1t-1} + b_{12}(\theta)q_{2t-1}, \qquad (6.1)$$

$$q_{2t} = c_2(\theta) + a_{21}(\theta)|r_{1t-1}| + a_{22}(\theta)|r_{2t-1}| + b_{21}(\theta)q_{1t-1} + b_{22}(\theta)q_{2t-1}, \qquad (6.2)$$

or more compactly by:

$$q_t = c + A|R_{t-1}| + Bq_{t-1}, \qquad (6.3)$$

where q_{it} is implicitly defined as $\Pr[r_{it} \leq q_{it}|\mathcal{F}_{t-1}] = \theta,\ i = 1{,}2$. That is, quantiles of stock return series r_{it}, at level θ, depend on the first lag of the returns R_{t-1}[47], via the matrix A, and on the first lag of the quantiles in the bivariate system, via the matrix B. Notice that the elements in the main diagonal of B measure the dependence of the quantiles on its own lags. In contrast, elements outside the main diagonal measure the tail codependence between the quantile series.

Assuming one suitable exogeneity restriction in the system, it is possible to recover the structural innovations and, therefore, to calculate quantile pseudo impulse-response functions as proposed by White et al. (2015). Here, we use the fact that the US market can be taken as the origin of recent major shocks to the global financial markets, as documented by Ehrmann et al. (2011) and also the fact that this market mainly reacts to its own news, given its significant size and liquidity (Ehrmann et al., 2011; Brazys et al., 2015). In this

[47] An alternative specification of the model described in the main text consists of including squared returns, or other proxies for the volatility of the returns, instead of their absolute values. This approached has been recently explored, in the empirical application provided by Han et al. (2016), regarding their 'cross-quantilogram'.

way, while we impose the restriction that the US index is contemporaneously insensitive to external shocks, every other market reacts contemporaneously to the US index. This assumption remains a plausible and simple alternative in all cases, supported by the empirical literature, and it is much more suitable than assuming strict exogeneity of the global factors.

Pseudo impulse-response functions (PIRFs) differ from traditional functions because, unlike the latter where a one-off intervention δ is given to the error term ε_t, PIRFs assume that the one-off intervention δ is given to the observable return r_t only at time t. At all other times there is no change in r_t. In this way, the pseudo θth quantile impulse-response function for the i*th* return r_{it} is defined as:

$$\Delta_{i,s}(\tilde{r}_{it}) = \tilde{q}_{i,t+s} - q_{i,t+s}, \quad s = 1,2,3 \ldots T \tag{6.4}$$

where $\tilde{q}_{i,t+s}$ is the θth-conditional quantile of the treated series, $\tilde{r}_{it}$, and $q_{i,t+s}$ is θth-conditional quantile of the contra-factual series, r_{it}. One advantage of PIRFs $\Delta_{i,s}(\tilde{r}_{it})$ is that they retain the traditional interpretation of IRFs, even when they can be calculated for different quantiles of the distribution. In this way, they allow us to enhance the analysis of extreme codependences between pairs of time series, approaching the problem of estimating tail dependences in a direct fashion, instead of indirectly, by recovering them using models of the first and second conditional moments.

6.3. Data

We used MSCI daily stock price indexes, as calculated by Morgan Stanley between 30 June 1995 and 30 June 2015, giving a total of 20 years of transactions (5218 observations). All data were obtained from Datastream International. The period was selected primarily on the basis of data availability for the whole sample. These indices measure the price behavior of the assets traded on the stock market in each country, without accounting for dividends. They are constructed in a standard way for each country, which allows market prices to be compared. We transformed the original prices into logarithmic returns by taking natural logs and differentiating.

In the case of Latin America, we used the country indexes of Argentina, Brazil, Chile, Colombia, and Peru, the largest, most liquid markets in the region. We selected the markets of the G7 economies as a benchmark, and so used the MSCI indicators for the United Kingdom, Canada, Germany, France, Italy and Japan. We also worked with the US index constructed by Morgan Stanley.

The period analyzed was marked by several crises, frequently preceded by boom-bubble episodes in the global financial markets. For instance, the period witnessed the Argentine debt crisis of 2002; the Colombian crisis of 1999; the last part of the Mexican crisis, known as the 'tequila crisis' in 1994-1995; the

Asian crisis in 1997; the Russian crisis in 1998; the dotcom crisis in the US in 2000; the September 11 terrorist attacks; the global financial crisis from 2007 to 2009; and the European debt crisis in 2010, among others.

6.4. Results and Discussion

The events outlined above provided the motivation for our analysis of the time series quantiles[48]. Reactions to the shocks originating in the main global financial market in periods of pronounced rallies are expected to differ markedly from those experienced during economic crashes. Reactions may also differ between periods of normal and extreme economic activity. All these episodes are naturally related to different quantiles of the market return distributions.

Below, we test the hypothesis of statistical dependence between the series of quantiles for the different markets, with the US index serving as a pivot point. First, we present the results of the reduced form vector autoregression (VAR), followed by the results for the pseudo impulse-response functions following a structural shock to the US index. Finally, we introduce various performance tests and robustness exercises.

A. Reduced Form Vector Autoregression

Tables 6.1 and 6.2 provide a summary of the estimated coefficients for the six main Latin American and the six mature markets in the reduced form model. We present the coefficients associated with Equation 6.2 that best describe the relationship of each index with the US indicator. The coefficients a_{21} and b_{21} were estimated at three different quantiles of the distribution of returns: $\theta = \{0.01, 0.5, 0.99\}$, for each country. We also report the joint statistical significance of the coefficients outside the main diagonal of the matrixes A, B, in each case.

We estimated bivariate VAR models between the US index and each of the twelve market indicators. Although this approach runs the risk of incurring bias due to omitted variables, it has the advantage of allowing us to use the PIRFs provided by White et al. (2015) in our analysis.

[48] Nevertheless, we also tested for parameter instabilities in the linear model specifications, outline in footnote 4. In all the cases, both for emerging and mature markets (but Italy), we rejected the null of stability in favor of an alternative of structural changes. We used cumulative-sum (CUSUM) statistics and dynamic confidence bounds. The results are available upon request.

Table 6.1
Reduced form VAR coefficients at 50th percentile

	50%												
	c2	*a21*	*a22*	*b21*	*b22*	*js*		*c2*	*a21*	*a22*	*b21*	*b22*	*js*
Arg	0.00	0.00	0.01	-0.08	0.08	0.54	**Can**	0.00	0.00	0.00	0.00	0.00	0.01
	0.04	*0.02*	*0.01*	*0.70*	*0.76*			*0.00*	*0.00*	*0.00*	*0.70*	*1.20*	
Bra	0.00	0.00	0.01	-0.03	0.00	0.33	**Fra**	0.09***	0.00	0.00	-0.20	-0.94**	4.62
	0.03	*0.02*	*0.02*	*0.69*	*1.84*			*0.00*	*0.00*	*0.00*	*0.10*	*0.10*	
Chil	0.00	0.00	0.01	-0.04	0.02	2.03	**Ger**	0.15***	-0.07***	0.0	-1.5	0.1	17.73***
	0.02	*0.02*	*0.02*	*0.35*	*3.80*			*0.00*	*0.00*	*0.00*	*1.00*	*0.60*	
Col	-0.01	0.00	0.03	0.10	0.03	0.07	**Ita**	0.00	0.00	0.00	-0.30	-0.40	1.85
	0.02	*0.01*	*0.02*	*0.40*	*0.44*			*0.00*	*0.00*	*0.00*	*0.40*	*0.60*	
Mex	0.04	-0.01	0.02	0.07	-0.78***	1.02	**Jap**	0.00	0.00	0.00	0.00	1.00	1.50
	0.03	*0.02*	*0.01*	*0.15*	*0.24*			*0.00*	*0.00*	*0.00*	*1.00*	*1.60*	
Peru	0.03	0.00	0.03	-0.38	-0.27	0.84	**UK**	0.08***	-0.07***	0.00	-0.60	-0.50**	10.74**
	0.03	*0.02*	*0.02*	*0.51*	*0.66*			*0.00*	*0.00*	*0.00*	*0.40*	*0.30*	

Note: *** significant at 99%, ** significant at 95%, * significant at 90%. Reduced form VAR coefficients at 50th percentile. *c2* is a constant, *b22* is the autoregressive quantile coefficient, *a22* is the autoregressive mean coefficient, *a21* and *b21* are the autoregressive cross-coefficients and *js* is the statistic associated to the joint significance of the cross-coefficients.

The statistics in Table 6.1 highlight certain similarities between the emerging and the advanced economies included in our sample. For instance, if we focus on the transmission of shocks between markets in the 50th percentile (the median), we observe that the estimations of the cross-sectional effects, which relate the US market with the rest of the sample, tend to be non-significant. In the developed economies, only Germany and the United Kingdom show a negative and statistically significant coefficient a_{21}, as associated with Equation 6.2. The effects in the median, however, for the LA markets and the other mature economies are non-significant in all cases. The same result is found for the joint significance test (last column, Table 6.1).

The autoregressive coefficients, relating the median values with their own lags, are also insignificant in almost all cases (with the exceptions of France, Mexico and the UK). These results are consistent with the weak form of the efficient market hypothesis and support past evidence in the literature about the unpredictability of asset returns in the central fragment of the distribution, within a daily frequency framework (White, 2000; Christoffersen and Diebold, 2006).

Table 6.2
Reduced form VAR coefficients at 1st and 99th percentiles

	1%						99%					
	c2	*a21*	*a22*	*b21*	*b22*	*js*	*c2*	*a21*	*a22*	*b21*	*b22*	*js*
	Latin American Stock Markets											
Arg	-0.17**	-0.16*	-0.35	-0.05	0.88***	17.71***	0.20*	0.02	0.31**	0	0.87***	5.28
	0.1	*0.11*	*0.19*	*0.03*	*0.05*		*0.11*	*0.13*	*0.13*	*0.06*	*0.03*	
Bra	-0.18**	-0.14	-0.28**	-0.06	0.89***	6.08	0.05	0	0.24***	0.03	0.89***	0.94
	0.11	*0.2*	*0.12*	*0.05*	*0.05*		*0.06*	*0.11*	*0.05*	*0.06*	*0.02*	
Chi	-0.12**	-0.08	-0.39***	-0.04	0.86***	5.36	0.02	0	0.30***	0.03	0.87***	5.00
	0.05	*0.08*	*0.07*	*0.03*	*0.03*		*0.03*	*0.07*	*0.06*	*0.02*	*0.03*	
Col	-0.27***	-0.21	-0.58***	-0.08***	0.78***	18.52***	0.40***	0.08	0.80***	0	0.63***	4.68
	0.06	*0.15*	*0.09*	*0.03*	*0.03*		*0.1*	*0.06*	*0.14*	*0.03*	*0.08*	
Mex	-0.03	-0.05	-0.09**	-0.01	0.96***	3.56	0.01	0.10**	0.22***	-0.03	0.93***	4.57
	0.04	*0.1*	*0.04*	*0.03*	*0.02*		*0.02*	*0.05*	*0.06*	*0.02*	*0.02*	
Per	-0.08***	-0.12	-0.27***	-0.04	0.91***	15.36***	0.06***	0.06	0.15***	-0.01	0.93***	3.64
	0.02	*0.08*	*0.08*	*0.03*	*0.03*		*0.02*	*0.07*	*0.02*	*0.02*	*0.01*	
	Mature G7 Stock Markets											
Can	-0.18**	-0.16	-0.34**	-0.05	0.88***	17.92***	0.21*	0	0.36**	0.01	0.86**	5.45
	0.1	*0.11*	*0.19*	*0.03*	*0.05*		*0.12*	*0.15*	*0.18*	*0.07*	*0.05*	
Fra	-0.16***	-0.13***	-0.21***	0.01	0.85***	16.58***	0.07***	0.14***	0.29***	-0.02	0.86***	27.32***
	0.04	*0.05*	*0.05*	*0.05*	*0.06*		*0.03*	*0.04*	*0.03*	*0.02*	*0.03*	
Ger	-0.15***	-0.12	-0.25***	0.03	0.83***	9.10*	0.04*	0.20*	0.14***	-0.04	0.92***	12.44**
	0.05	*0.07*	*0.05*	*0.02*	*0.04*		*0.03*	*0.11*	*0.03*	*0.03*	*0.04*	
Ita	-0.07	-0.11	-0.25	-0.04	0.92***	7.48	0.07***	0.08	0.14***	-0.02	0.94***	3.42
	0.08	*0.09*	*0.24*	*0.05*	*0.06*		*0.03*	*0.08*	*0.02*	*0.03*	*0.01*	
Jap	-0.55***	-0.39***	-0.38***	-0.03	0.65***	76.99***	0.09**	0.35***	0.19***	-0.09***	0.89***	110***
	0.13	*0.05*	*0.09*	*0.05*	*0.09*		*0.04*	*0.04*	*0.03*	*0.03*	*0.03*	
UK	-0.11**	-0.22***	-0.19***	0.05	0.78***	77.66***	0.03**	0.11***	0.11***	-0.03	0.95***	21.77***
	0.05	*0.08*	*0.04*	*0.22*	*0.27*		*0.01*	*0.04*	*0.02*	*0.02*	*0.02*	

Note: *** significant at 99%, ** significant at 95%, * significant at 90%. Reduced form VAR coefficients at 50th percentile. *c2* is a constant, *b22* is the autoregressive quantile coefficient, *a22* is the autoregressive mean coefficient, *a21* and *b21* are the autoregressive cross-coefficients and *js* is the statistic associated to the joint significance of the cross-coefficients.

Another common pattern that can be documented at this stage of the analysis (Table 6.2) is the fact that tail-codependences appear to be more significant in the lowest quantile than they are in the highest one, independently of whether the market is mature or emerging. Indeed, 8 out of 12 markets present statistically significant cross-dependence at $\theta = 0.01$ and only 4 out of 12 do so at $\theta = 0.99$ (see joint test results in columns 7 and 12). In other words, shocks experienced by the US market tend to lengthen the tails of the return distributions in the other markets in an asymmetrical fashion. In a related study, Baur and Schulze (2005) analyzed 11 markets in Asia and four aggregate regional indexes in Europe, LA, Asia and the USA and similarly documented a stronger dependence between extreme negative returns than between extreme positive returns. However, these authors do not provide statistics for the dynamics of the system after a shock, nor do they undertake specific comparisons between LA markets and markets in rest of the world.

The similarities found in the median of the distributions of advanced and emerging markets contrast with the differences found in their highest and the lowest quantiles. Recall that high quantiles (i.e., $\theta = 0.99$) are likely associated with bullish market episodes and financial bubble periods, in which sharp rates of growth in stock prices are recorded. In contrast, low quantiles (i.e., $\theta = 0.01$) are mainly associated with bearish markets, periods of crises and scenarios of financial distress. These lower quantiles, when calculated at very low levels, such as $\theta = 0.01, 0.05$, can be interpreted as Value at Risk (VaR) statistics.

Bearing this in mind, Table 6.2 makes evident that at $\theta = 0.99$ there is a greater codependence between the US and the mature markets than between the US and the LA markets. The joint hypothesis of quantile cross-dependence is maintained for Germany, the UK, France and Japan and it is rejected only in the cases of Canada and Italy.

If we examine the Latin American markets, a contrasting landscape emerges. In none of the six markets in our sample do we record a statistically significant cross-tail-codependence. Only Mexico exhibits an individually significant relationship in the case of the coefficient a_{21}. In all other instances, the autoregressive terms are statistically significant, but the codependence terms are not. This result indicates that there is a clear statistical dependence between the right tail of the marginal distributions in each market, but this dependence does not extend to the bivariate distribution. In other words, after a high-value realization in the returns of these markets, a high-value realization is expected to follow in the next period. However, this cannot be attributed to high (or low) realizations in the US market. This result contrasts with those recorded for most of the mature economies and is in line with previous findings in the literature that report a lower degree of financial interdependence between the LA and the global (and US) financial markets than that found with Western Europe markets (see Bekaert et al., 2005 and Bekaert et al., 2014).

It is also possible to analyze the left tail of the return distributions by inspecting the quantile in which θ equals 0.01 – that is, the 'Value at Risk' scenarios, the worst scenarios that can be expected during regular market conditions. Specifically, in 99% of occasions the returns are expected to be greater than the 1st estimated percentile. In such cases, the evidence of tail-codependence between the US market and the other developed markets in the sample is decisive. Indeed, 5 out of 6 mature markets exhibit tail-codependence when we take the joint hypothesis statistic (Table 6.1) into account. Only in the case of Italy can the cross-dependence be disregarded. In the emerging Latin-American economies the evidence is more balanced. While tail-dependence is significant in the cases of Colombia, Peru and Argentina, it is not in those of Brazil, Chile and Mexico. This scenario is consistent with hypotheses forwarded in the literature that highlight the importance of amplifying mechanisms during crises, which induce contagion during episodes of financial distress. Although the argument has been made within a market (Brunnermeier and Oehmke, 2013), the same mechanisms could be operating at an international level.

B. Structural VAR - Pseudo impulse-response functions

The analysis of the PIRFs at different quantiles substantiates the interpretation of the results above. We constructed PIRFs for each market, after identifying a structural shock as two standard deviations from the US index. Using the Cholesky factorization, we assume that the US is contemporaneously exogenous in each bivariate system.

The main results for the LA markets are presented in Figure 6.1 while Figure 6.2 shows the mature economy benchmarks. While the results are in line with the previous discussion, the PIRFs tend to be statistically significant in most cases with the exception of the central cases (associated with the medians of the distributions, which are not reported for reasons of space). These impulse-response functions have the advantage of allowing the observation of the time persistence of the shocks as well as the direction of the effects at each specific quantile.

An interesting trend clarified by observing the PIRFs is the fact that the two-standard deviation shock to the US market induces effects with opposite signs depending on the quantile. This observation holds in all cases, regardless of whether the market is mature or emerging. This means that a sizeable positive shock to the US index increases the probability of a very high or a very low observation in the other markets. Thus, a shock increases the highest and lowest quantiles by enlarging the whole support of the unconditional return distributions. In other words, conditioning on a specific quantile we find that, while in higher quantiles the shock produces a positive response, this is related to a negative effect in lower quantiles.

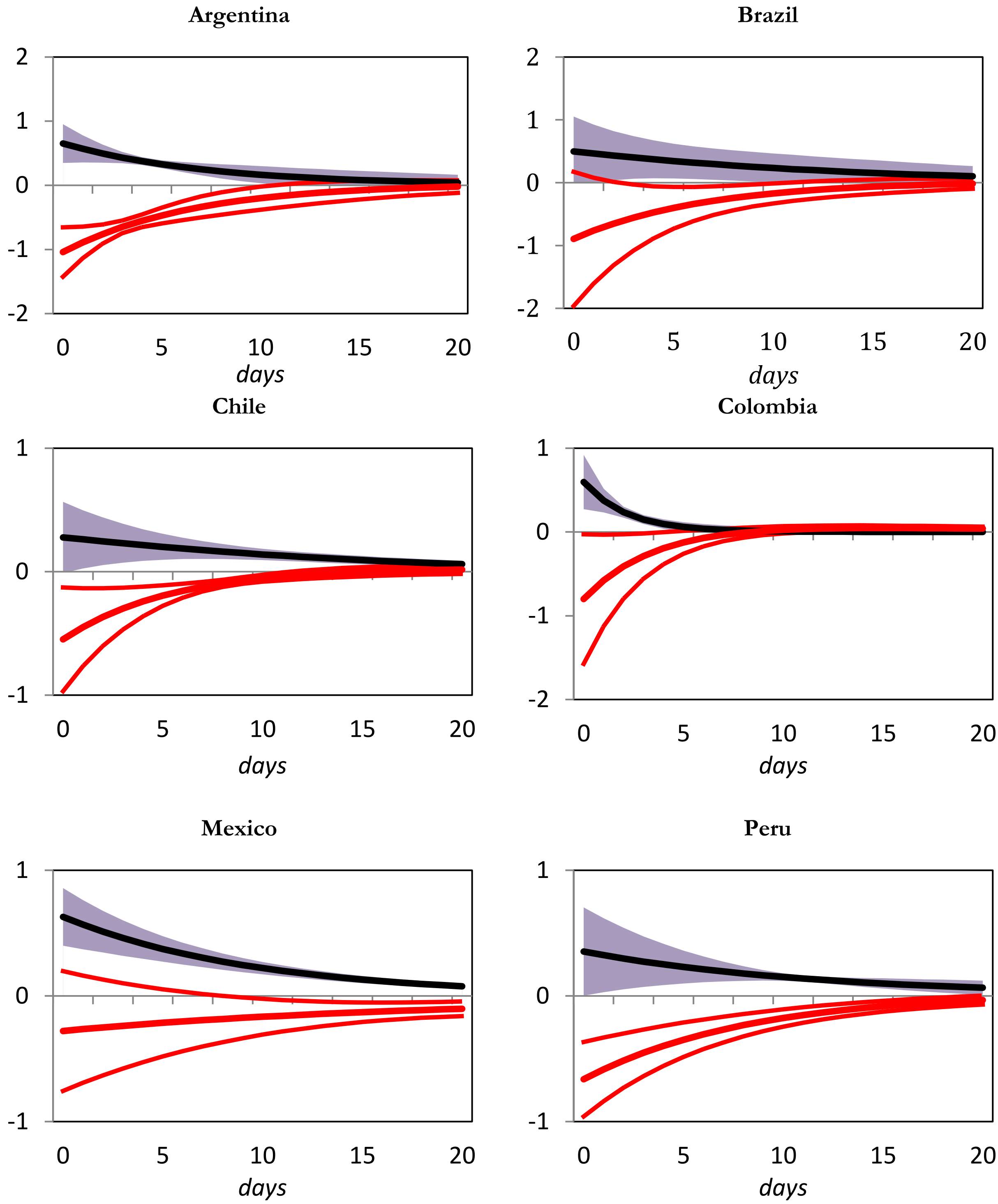


Figure 6.1. Impulse-response functions of the LA markets to a two-standard deviation shock in the US market. Note: The solid top line is the response at the 99th percentile, and the corresponding 95% confidence interval is the shaded area. The solid lower line is the response at the 1st percentile and the dotted lines are the corresponding confidence intervals.

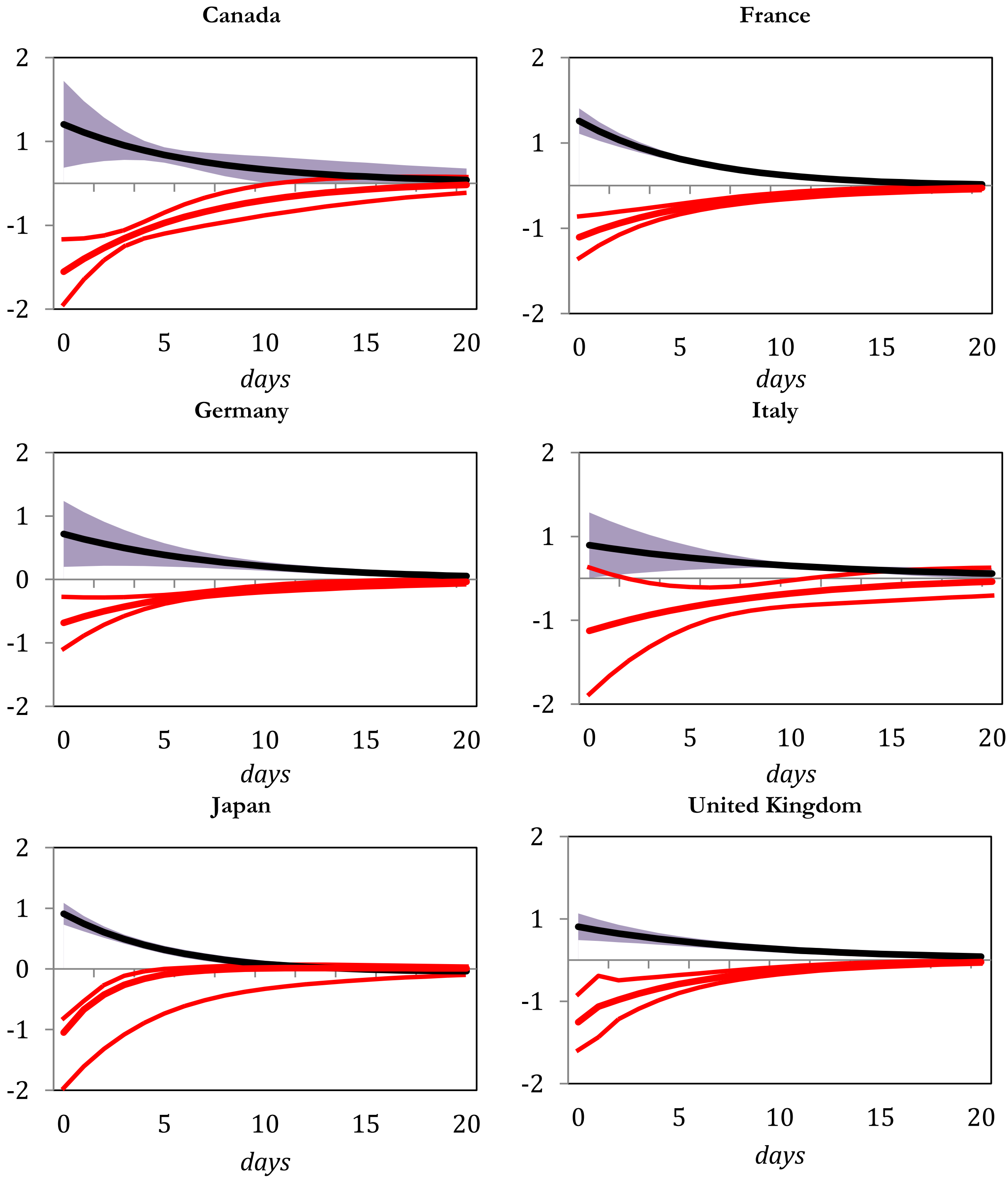


Figure 6.2. Impulse-response functions of the G7 markets to a two-standard deviation shock in the US market. The solid top line is the response at the 99th percentile, and the corresponding 95% confidence interval is the shaded area. The solid lower line is the response at the 1st percentile and the dotted lines are the corresponding confidence intervals.

These results also present novel empirical evidence in favor of different trading strategies, depending on the location of an observed market realization among the quantile categories. Although it would be optimal to go long in developed or emerging markets in the highest quantiles, after a positive shock to the US market is observed, the strategy would be inappropriate in the lowest quantiles. Indeed, the opposite may well be the optimal course in such a scenario.

The methodology employed here also allows us to identify asymmetries in the size of the effects, and not just in the signs of the tails. For instance, Japan presents a clear case of asymmetry. Thus, while the shock reduces the 1st percentile by 2.62 percentage points (pp), in the following 20 days it increases the 99th percentile by 4.25 pp in the same amount of time. This same pattern is documented in the case of Mexico (-3.57 pp in the left tail versus 5.56 pp in the right tail); however, several markets present asymmetries in the other direction. That is, in the cases of Canada, Peru and Argentina the shock decreases the lowest quantiles by -6.62 pp, -4.94 pp, and -6.60, respectively, while it increases the highest quantiles by only 1.28 pp, 3.54 pp and 4.76 pp.

The sign asymmetries documented in all markets can be related to episodes of flight-to- quality in the lowest quantiles and possible liquidity spillovers in the highest quantiles. Flight-to-quality refers to an environment in which investors seek to sell assets that are perceived as risky and to purchase safe assets instead (Caballero and Kurlat, 2008). In a global financial market characterized by a very limited supply of financial instruments considered liquid by the international investors during episodes of financial distress, (Caballero et al. 2008), it is not surprising that a positive shock to the US market, which increments the VaR in the other markets, will be followed by flows in the direction of the central economy, which is considered less risky, by all standards.

On the other hand, although a liquidity spillover is sometimes referred to in the literature as a situation of illiquidity in one market that is transmitted to the other market, we use the term here to refer to an episode in which excess liquidity in one market (presumably that of the US) increases the liquidity in the other markets. The high liquidity increases the amount of trading and purchasing taking place in markets other than that of the US, as investors look for profitable opportunities around the world and seek to avoid abnormally low interest rates in US government-backed securities and other assets.

In short, at low quantiles following a positive shock to the US markets, capital prefers to migrate to this market, increasing the likelihood of a loss in the other markets; in contrast, at high quantiles, a positive shock to the US market possibly reflects greater liquidity in the global economy, which can potentially overshoot to other markets, especially the more highly developed markets, but to some extent also to those in the emerging economies. Thus, the statistic is a suitable tool for measuring contagion episodes driven by flight-to-quality considerations or episodes of increasing correlation between markets, due to high liquidity levels in the global economy.

Note also that the differences in the responses are considerable within our sample, even within the Latin American zone. This points to the need for a careful analysis of the idiosyncrasies of each market before exploiting opportunities for diversification. For instance, Chile appears to represent a good opportunity for diversification most of the time: it does not present tail codependence in its high, median and low quantiles with the US markets, and the cumulated effect of the PIRFs is one of the smallest in the sample. In contrast, although Colombia, Peru and Argentina seem insensitive to the US market shocks in their highest quantiles, they are strongly affected in their lowest quantiles (financial distress episodes), which makes them less suitable locations for portfolio diversification during times of crisis.

Note as well that those results can be directly interpreted as risk (or volatility) spillovers from the US market to Latin American markets, since the returns are included in the reduced form model, in absolute values, in equations 6.1 and 6.2.

Finally, regarding the persistence of the shocks in the markets, we first counted the number of days during which the shock remained statistically different from zero in each market. We then counted the number of days after which at least half of the shock's total impact (i.e., its half-life) had been absorbed (Table 6.3). In this way we can draw meaningful comparisons between the markets. Interestingly, the half-lives of the shocks in the LA and mature markets are very similar. The half-life median in bearish markets, both in mature and LA markets, is four days, while the half-life median in bullish markets is six days in emerging and five days in mature markets. In both cases there is a slight asymmetry, with the shocks being more persistent during positive extreme return scenarios than during negative extreme returns. On an individual basis, the market that houses the shortest persistence is Colombia, with two days in both tails (very similar in this respect to Japan). In contrast, Chile reaches nine days in the 99^{th} percentile and Mexico and Peru seven days, in the same tail.

Table 6.3
Persistence (half-life in days)

	1%	*99%*		*1%*	*99%*
Argentina	4	4	**Canada**	4	4
Brazil	3	4	**France**	5	4
Chile	3	9	**Germany**	4	5
Colombia	2	2	**Italy**	4	6
Mexico	9	7	**Japan**	2	3
Peru	5	7	**UK**	4	6

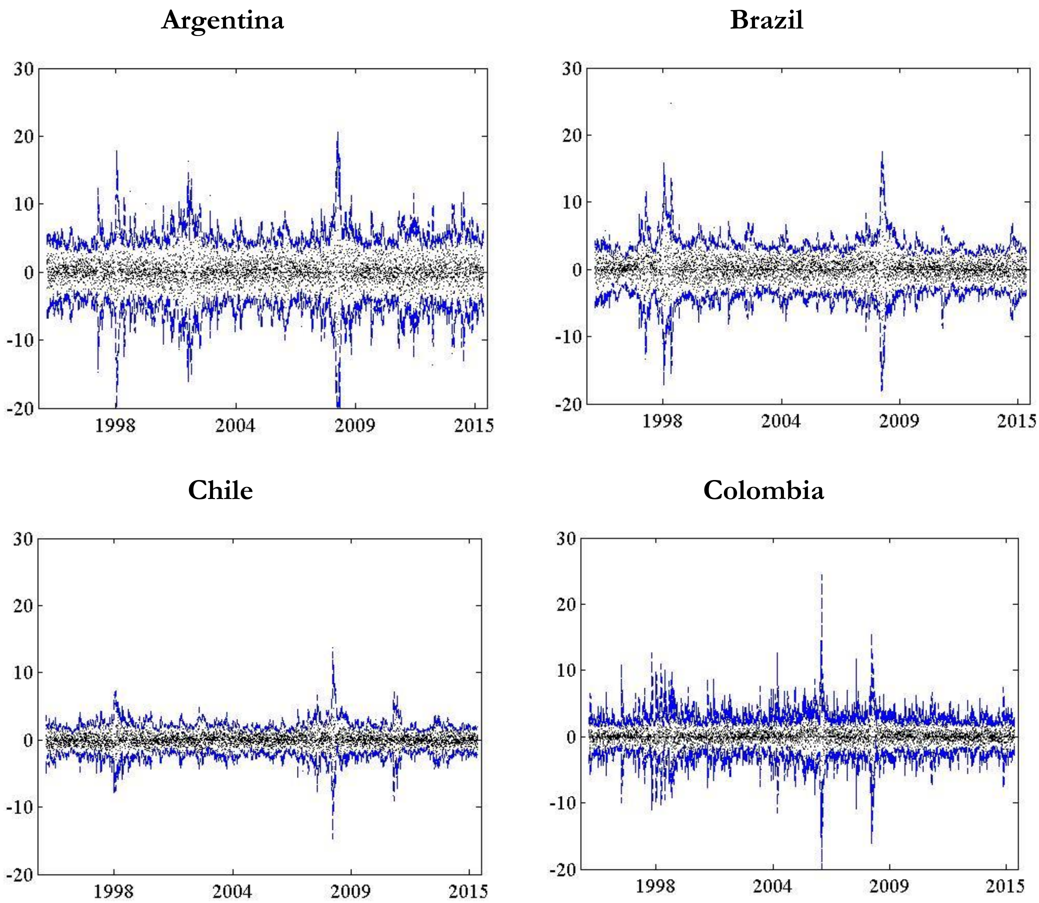
Note: half-life of the shocks, in days, for different markets.

C. Performance tests

In this section we assess the overall performance of the models at $\theta = \{0.01, 0.99\}$. This is possible by counting the number of exceedances of the actual returns above the highest quantile, and the number of exceedances below the lowest quantile. As usual, provided that we are constructing the quantiles at 1 and 99 per cent, we expect a number of exceedances in each case of around 1% of the times.

We present the returns of the markets and the estimated quantiles for the LA markets in Figure 6.3 and for the G7 markets in Figure 6.4. We also present the percentage of exceedances in Table 6.4.

As can be seen by visual inspection of the figures, and also by observation of the statistics in Table 6.4, the performance of the models appears to be highly satisfactory, both in the highest and lowest quantiles. We found percentages of exceedances in line with theoretical expectations for the selected confidence level, ranging from 0.98 to 1.02, with a mean value of 0.998.



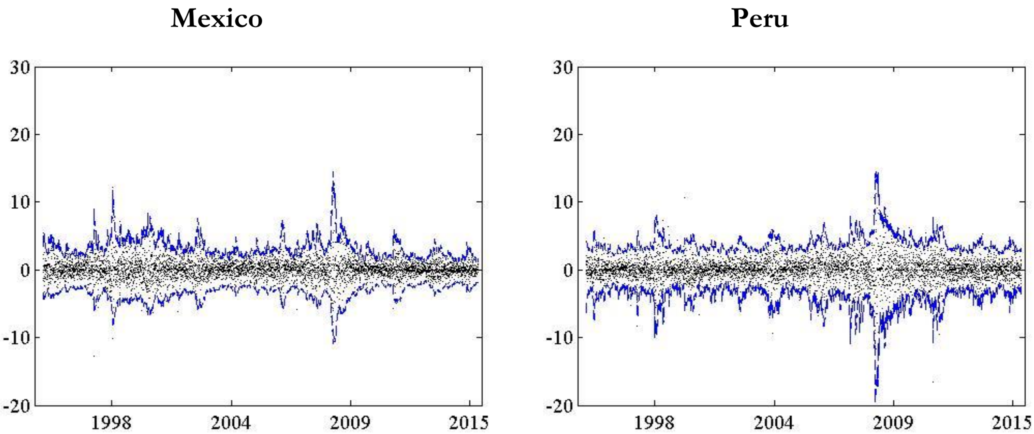
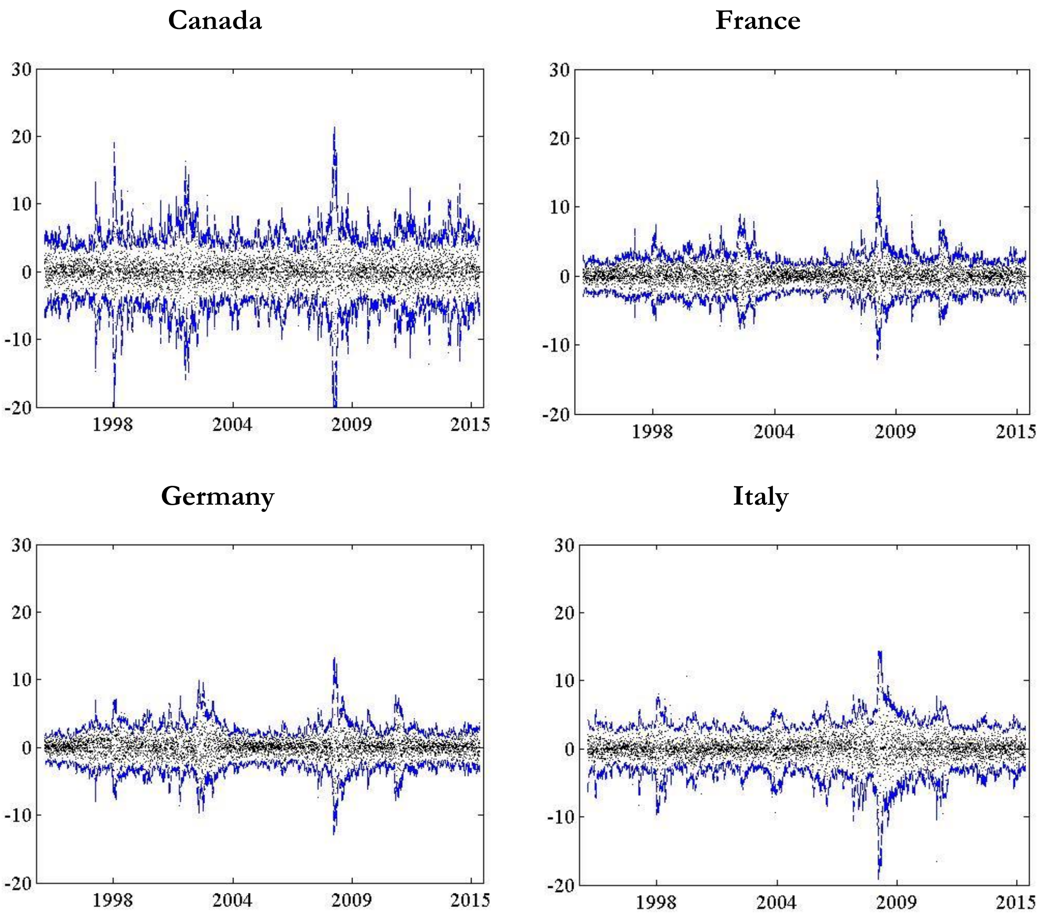


Figure 6.3. 1st and 99th percentiles and stock returns for Latin American markets: Time series of stock returns and quantiles at $\theta = 0.01$ and $\theta = 0.99$. The dotted blue lines can be interpreted as VaR statistics at the right and left tails with a 99% of confidence.



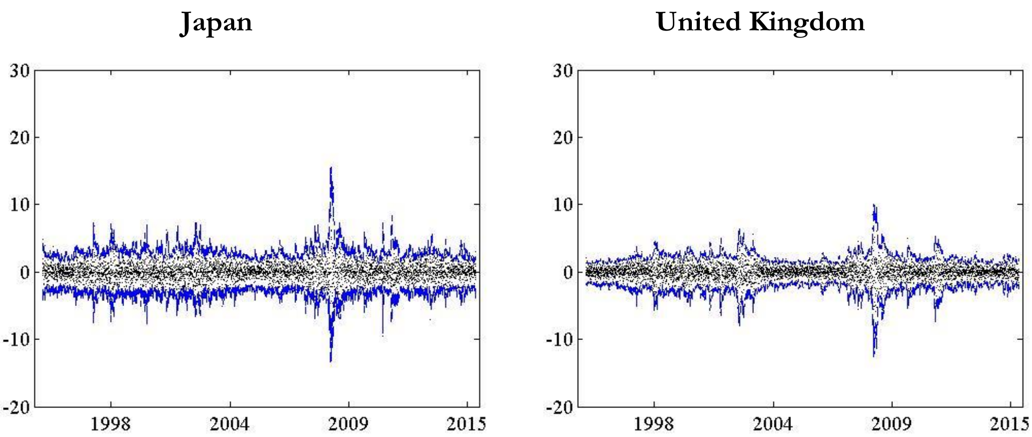


Figure 6.4. 1st and 99th percentiles and stock returns for G7 markets: Time series of stock returns and quantiles at $\theta = 0.01$ and $\theta = 0.99$. The dotted blue lines can be interpreted as VaR statistics at the right and left tails with a 99% of confidence.

Table 6.4
Percentage of Exceedances

	1%	*99%*		*1%*	*99%*
Argentina	1.00	1.00	**Canada**	1.00	0.98
Brazil	1.02	1.02	**France**	1.00	1.00
Chile	1.02	1.00	**Germany**	1.00	1.00
Colombia	0.98	1.02	**Italy**	0.98	1.00
Mexico	0.98	1.02	**Japan**	1.02	1.00
Peru	0.98	0.98	**UK**	1.02	1.00

Note: Percentage of exceedances of stock returns above percentile 99th and below the 1st percentile. It is expected a percentage of exceedances similar to 1% in the two cases. The calculations highlight the accuracy in the construction of both the high and the low quantiles.

D. *Implications for asset allocation*:

There is not doubt that the principle of portfolio diversification as introduced by Markowitz (1952) is one of the most influential insights in contemporaneous finance. Both, practitioners and academics have definitively embraced it. Nevertheless, authors such as French and Poterba (1991) and Vanguard (2014) have documented a persistent 'higher than optimal' share of domestic stocks in portfolios of global investors, which seem reluctant to hold well-diversified portfolios, on a global basis.

Here we provide the basis for the developing of trading strategies that benefit from international diversification in LA markets, in a very simple and plausible fashion. We document diversification benefits in previously unaccounted ways: first, we show diversification benefits that appear only during extreme market scenarios (either at very high or very low quantiles of the stock market returns); second, we isolate the effect that a US market shock induces on several markets, making it possible to compare their reactions and therefore, to identify less risky investment allocations, during turbulent episodes.

These results are particularly appealing in a scenario of increasing global stock returns correlations, which has made more difficult to achieve traditional portfolio diversification benefits, especially for investors with short-term horizon preferences (see Viceira et al. (2016)). Our exercise relies on the identification of structural innovations in the market. And therefore, it gives us insights that are not possible to extract from alternative reduced-form approaches such as traditional covariance analyses (or even more general formulations to measure dependence such as copula or dynamic copula models). That is, we construct a counterfactual scenario of each market dynamics following a shock to the US stock market. Disentangling such effect is simply not possible by recurring to the reduced-form alternatives.

In Table 6.5 and 6.6 we inform simple trading strategies that allow minimizing market-risk during extreme market scenarios, following a sizeable shock to the US market. In Table 6.5 we report the historical VaR at 99% of confidence for the left tail of the stock returns distribution. Then we report the cumulated loses at different horizons that an investor may expect to experience in each market, after a negative shock has impacted the US market. In Table 6.6 we report the same for the right tail.

As can be seen, in general, highest diversification opportunities can be achieved by investing in LA markets, compared to the mature markets. The only exception is Argentina that seems particularly sensitive to US shocks, especially at the lower tail and, on the side of the mature markets, Japan, which constitutes a very good diversification alternative in market distressed scenarios (the left tail).

However, the diversification opportunities depend on the preferred investment horizon of an asset manager. In other words, the cumulated loses are of different sizes, depending on the number of days elapsed after the original shock has been observed. Thus, different markets constitute a more appropriate investment, seeking to reduce the total risk of the portfolio; depending on how many days the investor will hold a given position.

For instance, in a situation of market distress, which can be easily identified as observing a return above the historical VaR (in absolute terms), with an investment horizon of 1 day, the best alternative is to invest in Mexico, which houses the lowest potential lost in the sample. For an investment horizon of 20 days the best alternatives are Chile and Colombia. Notice that, for example, the situation is very different for Colombia under these two horizons. After one day, Colombia experiences one of the highest loses in the LA countries, but due to the lack of persistence of the shock, the situation reverts after 20 days. Chile represents an attractive diversification opportunity, both, at left and right tails.

Table 6.5
Cumulated loses after a shock to the US market (left tail)

	VaR 99%	1 day	5 days	10 days	20 days
Japan	3.534	-1.049	-2.567	**-2.739**	**-2.622**
Germany	4.440	-0.684	-2.562	-3.745	-4.581
UK	3.191	-0.754	-2.553	-3.632	-4.307
France	4.068	-0.606	**-2.261**	-3.287	-3.975
Italy	4.376	**-0.626**	-2.496	-3.839	-4.862
Canada	3.448	-1.054	-3.939	-5.677	-6.623
Brazil	5.007	-0.895	-3.341	-4.818	-5.634
Chile	2.708	-0.548	-1.906	-2.542	-2.641
Colombia	3.519	-0.800	-2.272	-2.500	**-2.079**
Mexico	3.914	**-0.279**	**-1.259**	**-2.227**	-3.573
Peru	4.779	-0.663	-2.613	-3.970	-4.940
Argentina	6.296	-1.041	-3.897	-5.630	-6.598

Note: The first column shows the historical simulated VaR at 99% of confidence. Columns 2 to 5 show the cumulated loses after a show to the US market. The lowest loses are highlighted in for each horizon.

Table 6.6
Cumulated loses after a shock to the US market (right tail)

	VaR 99%	1 day	5 days	10 days	20 days
Japan	3.355	0.909	3.149	4.172	4.251
Germany	3.750	0.717	2.849	4.384	5.613
UK	3.045	**0.404**	**1.635**	**2.564**	**3.390**
France	3.642	0.756	2.745	3.867	4.453
Italy	3.585	0.396	1.647	2.663	3.672
Canada	3.180	0.704	2.680	3.972	4.912
Brazil	4.818	0.497	2.162	3.648	5.311
Chile	2.584	**0.277**	**1.231**	2.109	3.109
Colombia	3.683	0.596	1.451	**1.601**	**1.628**
Mexico	4.146	0.629	2.583	4.116	5.556
Peru	4.447	0.353	1.499	2.477	3.541
Argentina	5.961	0.652	2.525	3.798	4.765

Note: The first column shows the historical simulated VaR at 99% of confidence. Columns 2 to 5 show the cumulated loses after a show to the US market. The lowest loses are highlighted in for each horizon.

6.1. Conclusions

We document common and divergent patterns in reactions in LA and mature markets to a sizeable shock in US stock market returns. On the one hand, both the LA and mature markets in our sample show asymmetrical responses to the US market shock, dependent on the quantile analyzed. Following a positive shock in the US market, a positive effect is expected on the return distribution, provided the market is around the highest quantiles ($\theta = 0.99$). In contrast, at the lowest quantiles ($\theta = 0.01$), a positive shock to the US index produces a negative response in the other markets. We relate this first result to considerations of international liquidity overshooting, and the second to flight-to-quality effects among the US market and global financial markets.

A different interpretation is possible if we consider the unconditional distribution of the stock returns, without focusing on specific quantiles. In this case, what we find is that a positive shock to the US market is followed by a significant increase in the VaR statistics of the rest of the world sample, i.e., a risk increment. Nevertheless, the increments in the tails of the distributions follow irregular patterns, which depend on the idiosyncratic markets. For instance, while the increments in the right tail are higher for Japan and Mexico, the opposite is the case for Canada, Peru and Argentina.

Finally, we document a weaker tail-codependence among the LA markets in our sample than among the mature markets (except Argentina) with respect to the US index, as indicated by both the coefficients of the reduced form VAR and the highest value of the PIRFs. This points to possible diversification strategies that could exploit investments in the LA markets following a shock to the US market.

However, the differences within the LA sample are notorious. While Chile and Colombia appear to represent good diversification strategies both in times of crisis and during economic rallies, Peru and Argentina present higher tail-codependences during bearish scenarios than they do during bullish scenarios with regard to the US market. This makes them less suitable for diversification, especially during times of economic trouble, when diversification opportunities are more valuable for global investors.

In future research, it would be interesting to extend the cross-country comparisons performed here to include other emerging and developed economies. In this way, it would be possible to analyze global diversification strategies beyond the LA markets, using an endogenous multivariate setting. A further avenue for future research would be to incorporate more factors into the model structure, in addition to the US market index; however, this would require major extensions to the estimation process of the PIRFs and the MVMQ model, in general. Finally, further risk-diversification benefits could be explored within the region, which would require analyzing spillover across all LA markets and not only from the US market.

Conclusions

This dissertation contributes to the resolution of two fundamental problems in economics and finance: i) what is macro and financial uncertainty? How to measure it? How is it different from risk? How important is it for domestic and international financial markets? And ii) what sort of asymmetries underlie the international propagation of financial risk and uncertainty? That is, how risk and uncertainty propagation changes according to factors such as market states or market participants. The first part of this thesis (chapters 2 to 4) provides answers to the former questions, while the second part examines the latter (chapters 5 and 6). This study has implications for asset pricing, risk management, financial stability, and the optimal design of monetary and macroprudential policies.

In chapter 2, I empirically study the relationship between macroeconomic uncertainty and momentum abnormal returns. I show that high levels of uncertainty in the economy negatively impact the returns of a portfolio that consists of buying previous winners and selling previous losers, in the stock market. Uncertainty acts as an economic regime that underlies abrupt changes over time of momentum returns. The main pragmatic recommendation to be derived is not to trade momentum when uncertainty is above a certain threshold. Nevertheless, beyond this direct implication for trading, the study of momentum strategies, which are precisely based on extrapolating the immediate past in order to predict the immediate future, offers a unique opportunity to analyze the fundamental differences between risky and uncertain situations.

In chapter 3, I perform a systematic examination of several proxies for uncertainty in the literature, and propose an uncertainty index, built on stock market data. This proposal has several advantages over the competing alternatives, for example its higher frequency and the reduced computational costs for regularly updating it. I use my uncertainty estimator to carry out an analysis of the way in which uncertainty impacts economic activity. I find that uncertainty impacts significantly economic activity, and I document a reduction and a subsequent rebound effect in investment dynamics following an uncertainty shock. In Chapter 4, I study the propagation of equity market uncertainty to the global stock market and analyze the role of uncertainty as a systemic risk factor for the global banking sector. I find that the effects of risk and uncertainty on banks returns have remained stable over the last decade, and that economic policy uncertainty is indeed a relevant driver of returns in the banking sector. I also provide a new simple tool to measure vulnerable financial institutions (as opposed to the popular category of systemically important ones).

In the second part of my thesis I emphasize the asymmetric nature of the international propagation of risk across financial markets, which depends, for instance, on the market state, or the market participants. In chapter 5 I show that FX markets house their own idiosyncrasies, which are not considered in traditional analysis of return and volatility spillovers in currency markets, which implicitly assumes that for any given country the situation is roughly the equivalent of facing depreciation or appreciation pressures. This assumption is at the very least controversial. Consistently, I propose quantile-based statistics of downside risk, and construct an index to monitor financial stability of FX markets, while I explain the asymmetric nature of risk resorting to liquidity considerations. I find that the least liquid currency markets tend to be more vulnerable and to transmit more shocks in the left tail of the distribution than is the case with volatility. This is fundamental for the correct assessment of systemic risk in currency markets and for monitoring financial fragility and distress in currency markets around the world. I also find that the most liquid currencies are generally net-transmitters of volatility during periods of US dollar appreciation, while the most liquid currencies are net-receivers of volatility in periods of turbulence lacking any clear trend.

Finally in the last chapter of my thesis, chapter 6, I explore the central role of the US stock market as a net-exporter of volatility to Latin American and G7 stock markets, while document important asymmetries in the international propagation of shocks during bullish and bearish markets, and for emerging and developed economies. I document a weaker tail-codependence among the LA markets in our sample than among the mature markets (except Argentina) with respect to the US. This points to possible diversification strategies that could exploit investments in the LA markets following a shock to the US market.

It is worth to add, in the sake of future discussion, that the sorts of asymmetries that I have considered in this thesis are also relevant for instance, for energy and insurance markets. Indeed, electricity markets are a good example in which the risk faced by suppliers and consumers are substantially different (Mosquera, Manotas and Uribe, 2017a), and where the negative or positive variations of prices are described in dissimilar ways by market fundamentals, such as weather (Mosquera, Manotas and Uribe, 2017b). Another example of the asymmetries that I investigate is found naturally in the context of insurance markets, in which mortality and longevity risks, from the perspective of insurance companies and pension funds on the one hand, and households on the other, are featured by different fundamentals and, therefore, should be measured in flexible and specific ways (Chuliá, Guillen and Uribe, 2017a,b).

The study of uncertainty and of risk nature and the asymmetric ways of their propagation across assets and markets is of paramount importance for the economics profession, yet it is still in its infancy. This dissertation is only an initial step in this direction, which I expect to explore in depth in the forthcoming years.

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