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Facing our (risk) aversions

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How to measure risk aversion?

We construct a new global risk aversion indicator by dynamically weighting risks among six aversion sectors, and unveil the relationships between risks and returns using causality graphs.

From risk proxies to a risk aversion indicator

We source from a large variety of risk proxies including VIX, credit spreads and FX implied volatility to construct sector risk aversion indicators. We then aggregate this information dynamically via non-negative matrix factorization, and evaluate causality among these indicators using Bayesian networks.

Risk regimes, economic regimes and asset returns

Using a Hidden Markov Model, we identify episodes of risk-on / risk-off regimes. We compare rates of true warnings and false alarms of our indicator, and evaluate its performance over historical crises.

To understand how interactions between risk regimes and macro-economic regimes affect asset returns, we also estimate global economic regimes based on the US short rates, term spreads and the US OECD leading indicator.

We are currently in a normal risk regime as well as a moderate economic environment.

Source: gettyimages.com

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A letter to our readers

Facing our (risk) aversions

This report serves as an attempt to answer some questions related to risk and risk aversion:

- How can we monitor risk aversion in financial markets?
- Is there a way to aggregate information from different asset classes into a single risk aversion indicator?
- How do asset returns behave under different risk regimes?
- Do risk regimes interact with macro-economic regimes? How sensitive are asset returns to these regimes?

We first review various risk proxies that have been employed in other studies on financial stress. We select a list of risk proxies for our risk aversion indicator based on data availability, data quality, rationale and discussions with our economists / strategists.

We then classify risk proxies into different risk aversion sectors, and assign dynamic weights to the sectors using non-negative matrix factorization (NMF). To ensure the proxies are comparable across sectors and over time, we explore several normalization approaches and choose to use Quantile-scores.

How high is high risk?

Armed with our risk aversion indicator, is it possible to distinguish normal regimes from risk-off / risk-on regimes? One could use a threshold, heuristically, chosen to produce crises with a certain frequency. Here, we suggest to systematically classify regimes using a Hidden Markov Model.

How “good” is our risk indicator? Based on a comprehensive chronology of historical crises, we compare the percentage of true warnings versus false alarms. We also use the area under the ROC curve to evaluate the accuracy of our indicator in identifying risk-off episodes.

Risk and returns…

Do asset returns behave differently across risk regimes? We investigate relationships between returns and risk via conditional distributions, Bayesian networks and Granger-causality tests. We also look into the interactions between risk regimes and macro-economic regimes and how they affect asset returns.

As always, we look forward to your insightful comments.

Yours sincerely,

Khoi, Vincent, Ada & Hemant

Deutsche Bank Asia Quantitative Strategy Team

What risk proxies to watch?

Since the Global Financial Crisis in 2008, there has been a surge of studies focusing on designing an indicator to monitor financial stress (e.g. Oet et al. 2011, Hollo et al. 2012). Financial stress is very general – it could refer to stock market crashes, a collapse in the banking sector, or a currency crisis in an emerging market.

To organize thoughts, we can first classify risk proxies into different risk aversion sectors. Within each sector, there can be different types of risk proxies: some are measures of volatilities, whether it is realized or implied. Some are measures of drawdown, e.g. CMAX, which is one minus the current price over the maximum price over the past 1 or 2 years (Coudert and Gex 2008). Another popular type of risk proxies are the interest rate spreads, which can reflect liquidity risk, funding risk and counter-party credit risk.

Risk proxies in different risk aversion sectors

Below is a table of potential risk proxies that one may employ in each risk aversion sector:

Figure 1: Types of risk proxies in each risk aversion sector

Risk aversion sectors	Volatilities	Correlations / beta	CMAX	Interest rate spreads	CDS
Financial sector	Realized vol of the idiosyncratic equity returns of bank index over market index	Financial beta	Financial sector crash	Bank bond spread	Banks Insurances
Money Market	Realized vol of Libor			TED spread Interbank cost of borrowing	Country
Equity markets	Equity implied vol	Differences between 4-year and 4-week stock-bond correlations	Stock market crash Non-financial stock market crash		
Bond markets	Realized vol of 10-year government bond index Implied vol of bond swaptions			Covered interest spread Corporate bond spread Liquidity spread Commercial paper over T-bill Treasury yield curve spread Emerging market credit spread, swap spread	Itraxx IG
Foreign exchange markets	Realized vol of exchange rates Implied vol of currency options Volatility spread of currency options Risk reversal of currency options		Weighted dollar crashes		
Commodity markets	Oil implied vol				

Source: Deutsche Bank Quantitative Strategy

Our choice of risk proxies

Borrowing from ideas in the literature, we decide to consider risk proxies that represent risks in the following 6 risk aversion sectors. These proxies are available with a daily frequency:

- Financial sector:
  - Spread of the credit default swaps (CDS) of 9 banks
  - Financial beta (MSCI Financials to MSCI World)
  - MSCI Financials CMAX
- Money market
  - US Ted spread
  - Swap spread (before 2008-09-30 since there are monetary interventions afterwards)
  - Bid-ask spread of US 3M
- Equity market
  - Equity implied vol: VIX, VSTOXX, VDAX
- Bond market
  - Implied volatilities of 3 government bond swaptions (USD, EUR, JPY)
  - Itraxx IG index
  - BAA Corporate bond spread
  - EM Sovereign bond risk
- Foreign exchange market
  - 5 FX Implied volatilities: CVIX, AUD/JPY, EUR/HUF, USD/BRL, USD/TRY
  - 3 pairs of FX volatility spread: USD/JPY, EUR/JPY and USD/JPY:
  - 2 pairs of risk reversals: USD/JPY and EUR/JPY
- Commodity market
  - Oil implied volatility

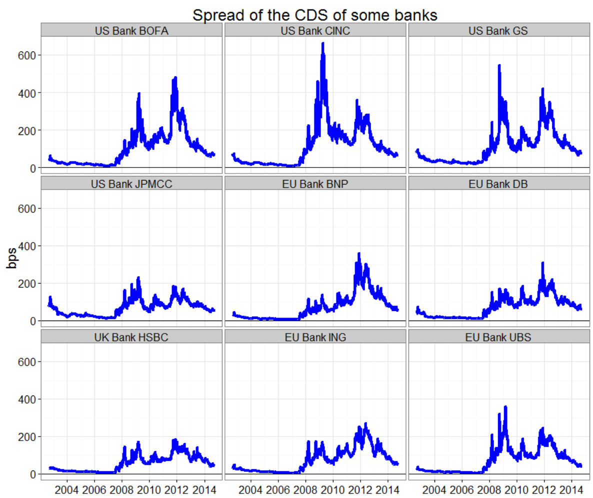
We provide below a description of these proxies, and discuss the rationale behind our choice.

Do CDS spreads react to crises?

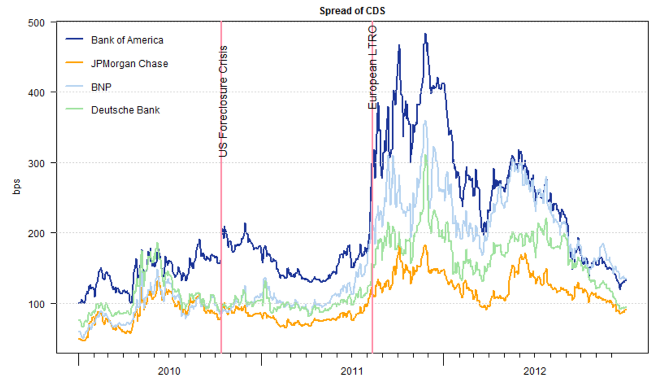
The CDS we consider have a maturity of 5 years. Figure 2 shows the spread of the CDS for the 9 banks in our risk proxy. We see that the variation of spreads over time can be large, especially during the Global Financial Crisis. In general, the CDS spreads become much higher after 2008 as compared to the period before.

We see that the spreads of CDS of the banks tend to spike in times of crisis. For example, during the US foreclosure crisis in 2010, the spread of the CDS of Bank of America increased from about 160 bps to over 200 bps. The reaction to the European LTRO (Long-Term Refinancing Operations) in 2011, when investor confidence fell to low levels, was even higher.

Figure 2: Spreads of the CDS in our risk proxies



Spreads of CDS increase significantly after the US Foreclosure crisis in 2010, and the European LTRO in 2011



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

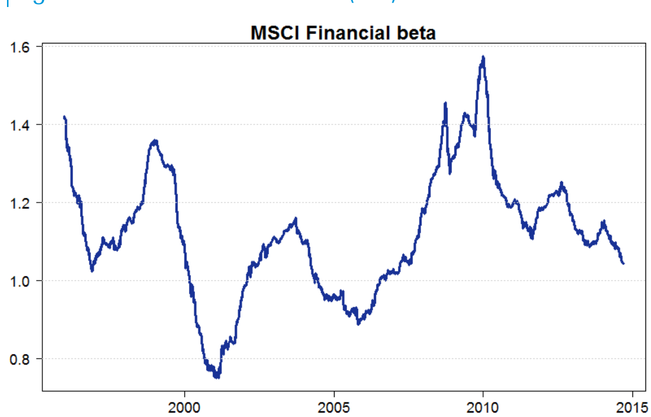
MSCI Financial beta

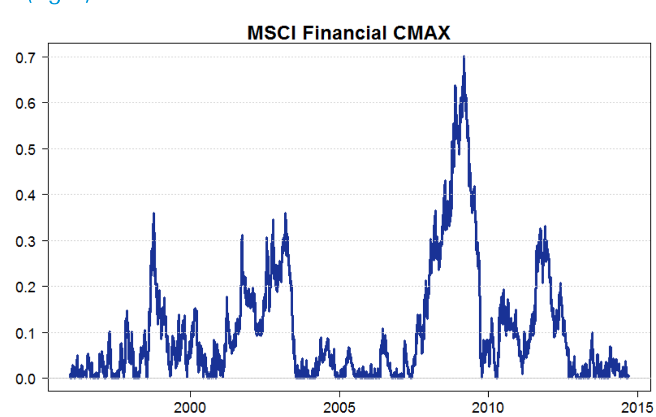
It is measured as the rolling 1-year beta of MSCI Financials to MSCI World. It can be regarded as a measure of the volatility of the financial sector relative to the market. Since the profitability of the banks is heavily affected by financial stress, their stock volatilities can reflect the strength of the financial sector.

MSCI Financial CMAX

CMAX is a measure of the maximum cumulated loss, which was first applied in Sarkar and Patel 1998, and has been included as a proxy for financial stress in various studies (Illing and Liu 2006, Hollo et al. 2012). CMAX can be measured for any asset. Here we apply it to the MSCI Financials to measure the stress in the financial sector.

Figure 3: MSCI Financial beta (left) and MSCI Financial CMAX (right)





Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

The TED spread

The TED spread is the spread between the rate of 3-month interbank loans and 3-month treasuries. It is typically used to capture short-term interest rate liquidity risk. As government rates are risk-free, the TED spread can be regarded as the risk of banks default. For example, during the Subprime crisis in September 2008, the TED spread was above 300 bps, whereas its historical average was around 30-50 bps.

The swap spread

The swap spread was commonly used as a risk indicator long before the Global Financial crisis. We use the US 10-year swap spread, i.e., the difference between US 10-year interest rate swaps and treasuries of comparable maturity. One can regard it as a proxy for credit risk and banks' willingness to lend to each other. A major factor that affects the swap spread is the slope of the yield curve, since it impacts the supply and demand for fixed versus floating payments (Mussche 2002).

However, since the Global Financial Crisis, we have observed more monetary interventions and swap spreads may no longer reflect risk that well. In 2010 and 2013, during the US debt ceiling debate, the risk of a technical US default increased, and the US 10-year swap spread was even negative (i.e., the treasury yield was higher than the swap rate). As such, we only include the swap spread as a proxy until 2008-09-30.

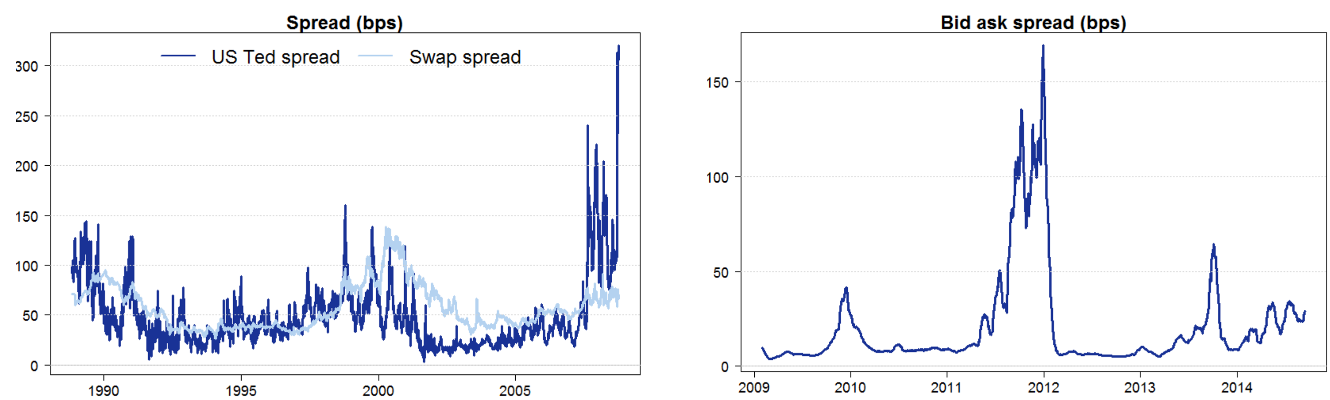
The Bid-ask spread

The bid-ask spread measures the difference in the bid price and ask price of the 3-month treasury bills. It captures the liquidity risk of the market. Before the Global Financial crisis, there was not much movement in the bid-ask spreads. It is only with the GFC that it began to spike during crises. As such, we include it as a risk proxy after 2009-02-01, which is just after its first spike in late 2008.

Equity implied volatilities

This is another popular measure for the volatility of stock markets. Here we consider a simple average of the 3 equity implied volatilities with the longest history: S&P 500 VIX, STOXX 50 VIX and DAX VIX. We do not include VIX from the Nikkei or KOSPI 200 since our understanding is that their movements can be overly affected by volatility trading.

Figure 4: US Ted spread, 10-year swap spread and bid-ask spread

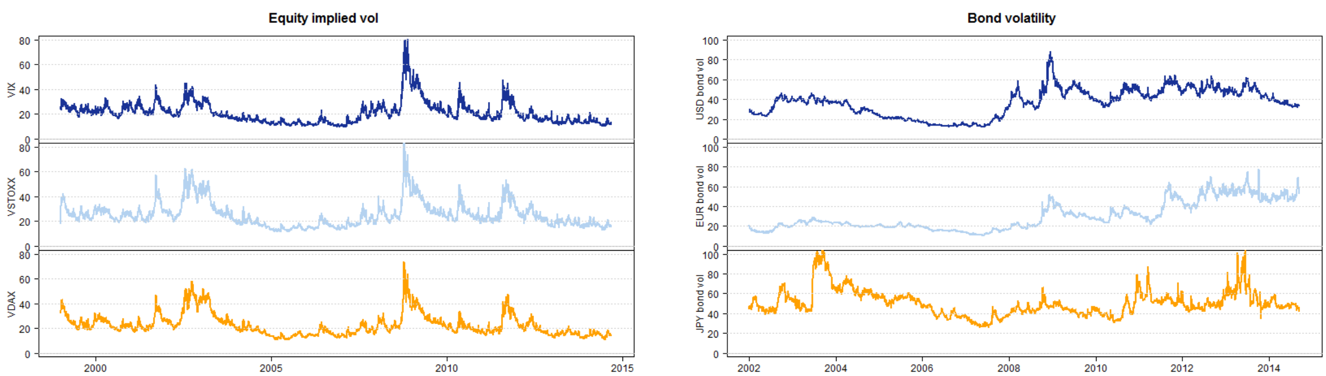


Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Bond volatility

Bond volatility is the average of the volatilities of government bond swaptions (3M-5Y) on USD, EUR and JPY bonds. Typically, during risk-off episodes, investors tend to pay more for protection against interest rate volatility. For EUR and JPY bond volatility, we ignore data before 2002 because of quality issues.

Figure 5: Equity implied vol (left) and bond volatility (right)



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Itraxx IG

Itraxx IG is a CDS index from MARKIT iTraxx Europe; it captures the credit risk of liquid European companies with investment-grade credit ratings.

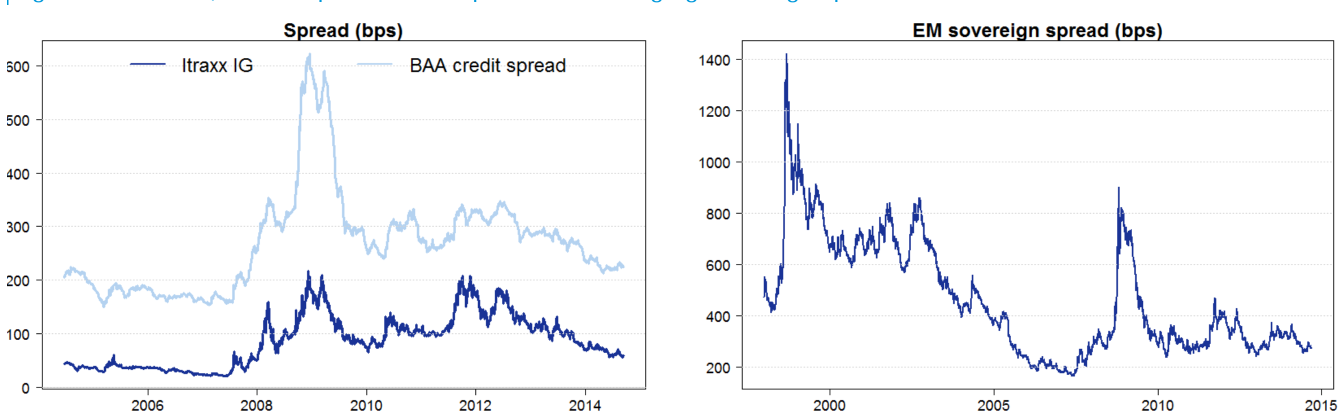
BAA Corporate bond spread

BAA Corporate bond spread is the spread between Moody's BAA yield and the US 10-year government bond yield. We could also have considered the A corporate bond spread, but it is highly correlated with the BAA corporate bond spread and has a shorter history.

Emerging sovereign risk

EM sovereign risk is measured by the EMBI JPMorgan Index. It reflects the evolution of bonds in the emerging market versus OECD bonds. It captures credit risks from emerging market.

Figure 6: Itraxx IG, BAA corporate bond spread and Emerging sovereign spread



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

FX implied volatility

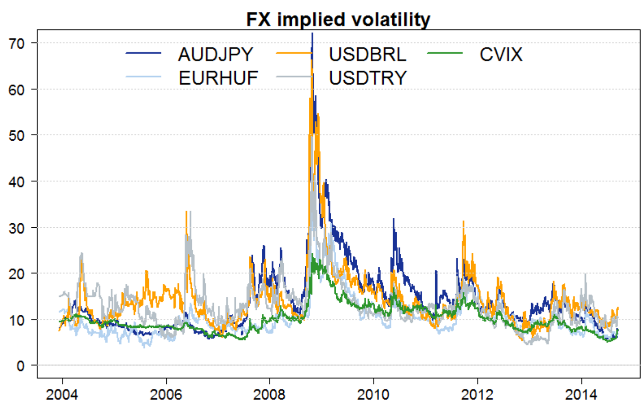
We take the simple average of 5 FX implied volatilities:

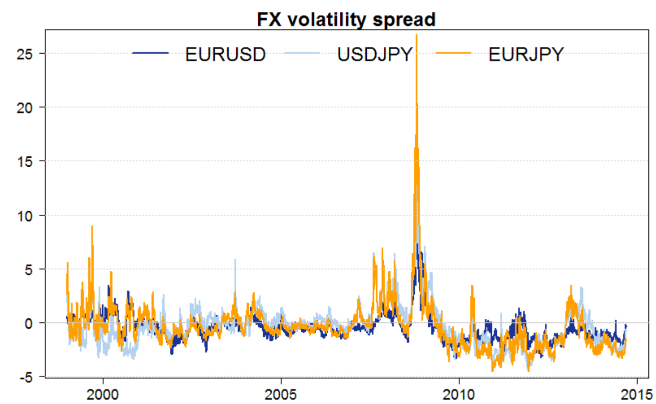
- The DB Currency Volatility Index (CVIX), which is the turnover-weighted implied volatilities of 9 developed market currency pairs[1];
- AUD/JPY, to capture carry trade risks;
- EUR/HUF, to capture peripheral European risk;
- USD/BRL and USD/TRY, to capture currency risks in emerging markets.

FX volatility spread

It is the term spread between 1-year and 1-month FX implied volatilities. Since it is the slope of the term structure, when the slope is more inverted, investors become more risk-adverse as they are willing to pay more for protection against short-term exchange rate volatility.

Figure 7: FX implied volatility and FX volatility spread





Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Risk reversal

Risk reversal, also called volatility skew, is often used in FX strategies. It is defined as the difference between the implied volatility of 1-month 25-delta OTM call options and that of the corresponding put options.

For example, if 1M 25-delta USD/JPY risk reversal is equal to 1, it means that the USD/JPY call option is one unit of volatility more "expensive" than the corresponding put options. This implies higher demand for call options, and hence USD over JPY.

Typically, a drop in risk reversal of USD/JPY indicates higher risk aversion. This is because JPY is regarded as a safe-haven currency and is the funding currency in carry trades. When risk aversion is high, JPY is more attractive, and put options on USD/JPY are more expensive[2].

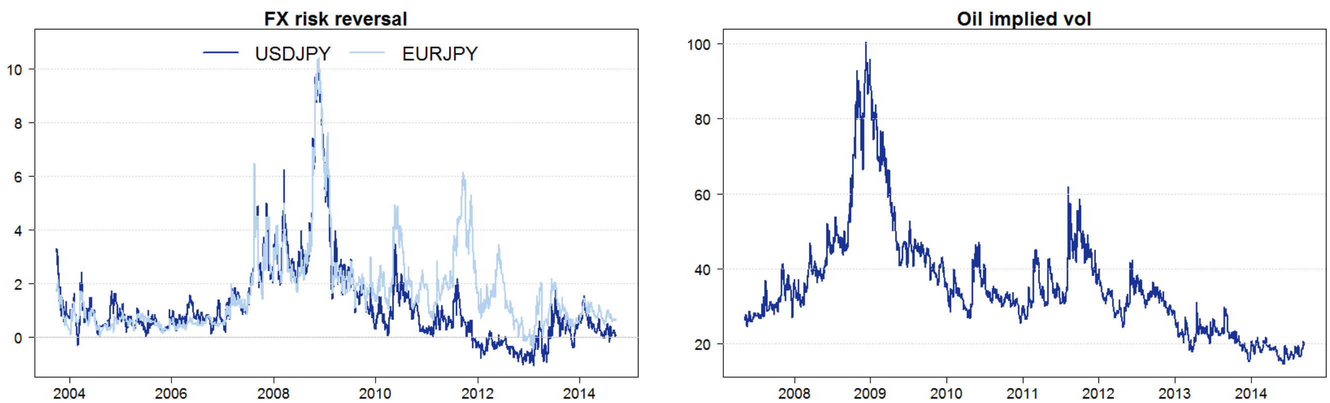
As such, we take the negative of the risk reversal of USD/JPY to proxy risk aversion. Similarly, we consider the negative of risk reversal of EUR/JPY.

[1] Saravelos, G. et al, Deutsche Bank Guide To Currency Indices, October 2007
[2] For more discussions of risk proxies related to currencies, please refer to De Bock (2013)

Oil-implied volatility

This does not seem to be a popular proxy used in the literature, probably due to its short history: it starts in late 2008.

Figure 8: FX risk reversal and oil implied vol



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 9 shows a summary table of risk proxies used in this report, and a comparison with those used in other studies.

Figure 9: Comparing our risk proxies with the ones used in other studies

		Cleveland Financial Stress Index (CFSI)	Canadian Financial Stress Index (FSI)	Composite Indicator of Systemic Stress (CISS)	Global Quantile Risk Indicator (GQRI)	Sentiment Indicator (SI)	Risk Aversion (RA)	Our Risk Aversion Indicator
No. of components		11	9	15	6	16	Over 60	15
Money markets	US TED spread	√		√		√	√	√
	Interbank cost of borrowing	√						
	Realized vol of LIBOR			√				
	MFI recourse to the marginal facility			√				
	Swap spread			√	√			√
	Bid-ask spread	√	√					√
Financial sector	MSCI Financials Index / MSCI World Index					√		
	CMAX of Financial sector			√				√
	Idiosyncratic volatility of bank equity returns			√				
	Bank bond spread	√	√					
	30Y /2Y Asset swap spread					√		
	Financial beta	√	√					√
	CDS						√	√
Foreign Exchange markets	Weighted dollar crashes	√	√					
	Implied Volatility				√	√	√	√
	Realized Volatility of currency pairs			√				
	IM / IY volatility spread					√		√
	Risk reversal					√		√
Credit markets	Covered interest spread	√	√					
	Corporate bond spread	√	√	√	√	√	√	√
	Commercial paper over Treasury bill spread	√	√					
	Treasury yield curve spread	√	√					
	Itraxx IG						√	√
	Bond volatility			√	√	√		√
	Non-financial CDS spread					√		
	Emerging market spread (EMBI Index)				√	√	√	√
Equity markets	CMAX of stock market index	√	√	√		√		
	VIX				√	√	√	√
	Realized Volatility of non-financial returns			√				
	4-year / 4-week stock-bond correlations differences			√				
Commodity markets	Oil implied volatility						√	√
Reference		Oet et al. (2011)	Illing and Liu (2006)	Hollo et al. (2012)	Luo et al. (2009)	Chen and Natividade (2012)	Guilleminot et al. (2014)	

Source: Deutsche Bank Quantitative Strategy

Risk aversion sectors

Normalizing our risk proxies

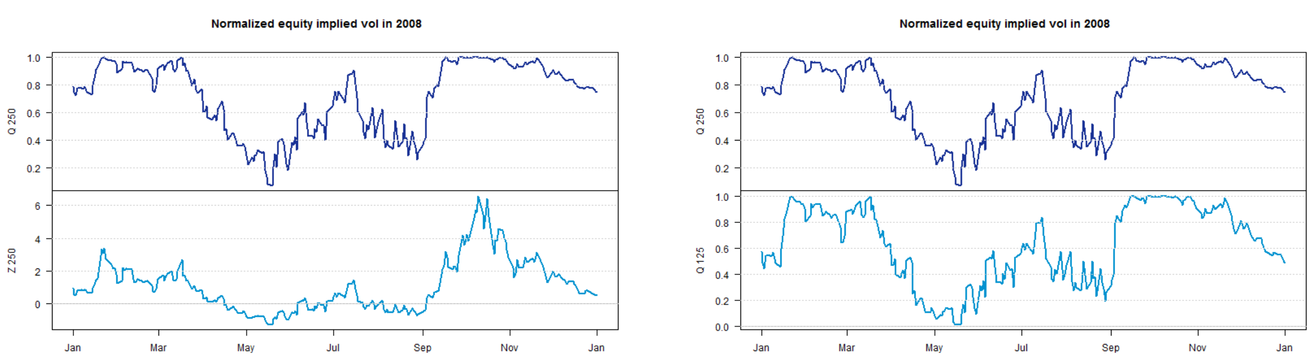
Our selected risk proxies have different ranges and volatilities. To ensure that they are comparable with each other, as well as comparable over time, we first need to normalize them. Some possibilities are:

- Q-score: Quantile scores are based on the empirical cumulative distribution function (CDF) of the variable and take values between 0 and 1. Extreme values will always be 0 or 1.
- Z-score: Removing the mean and scaling the variable by its standard deviation. This approach is suitable if the variables are normally distributed, and if we want to preserve some information anout the thickness of the tails of the distribution. However, z-scores are too sensitive when volatility is low. If there is a sudden shock, the z-score can surge to several standard deviations above the mean.
- P-score: The *p*-values of the z-scores, so that the transformed score is always between 0 and 1. This normalization gives results similar to the Quantile scores, but slightly smoother.

In the next sections, we discuss the aggregation / weighting approach for our risk aversion indicator; we advocate a method relying on positive variables. In addition, since the Quantile scores are easier to interpret than the P-scores and more popular in the literature, we decide to normalize our risk proxies using Quantile scores based on a 250-day rolling window. We have experimented with shorter rolling windows. Despite being more sensitive to crises, we find that shorter rolling windows lead to too many false alarms.

Figure 10: Different normalizations and rolling windows for equity implied volatility

Q 250 (top) versus Z 250 (bottom) | 250-day (top) and 125-day (bottom) rolling window

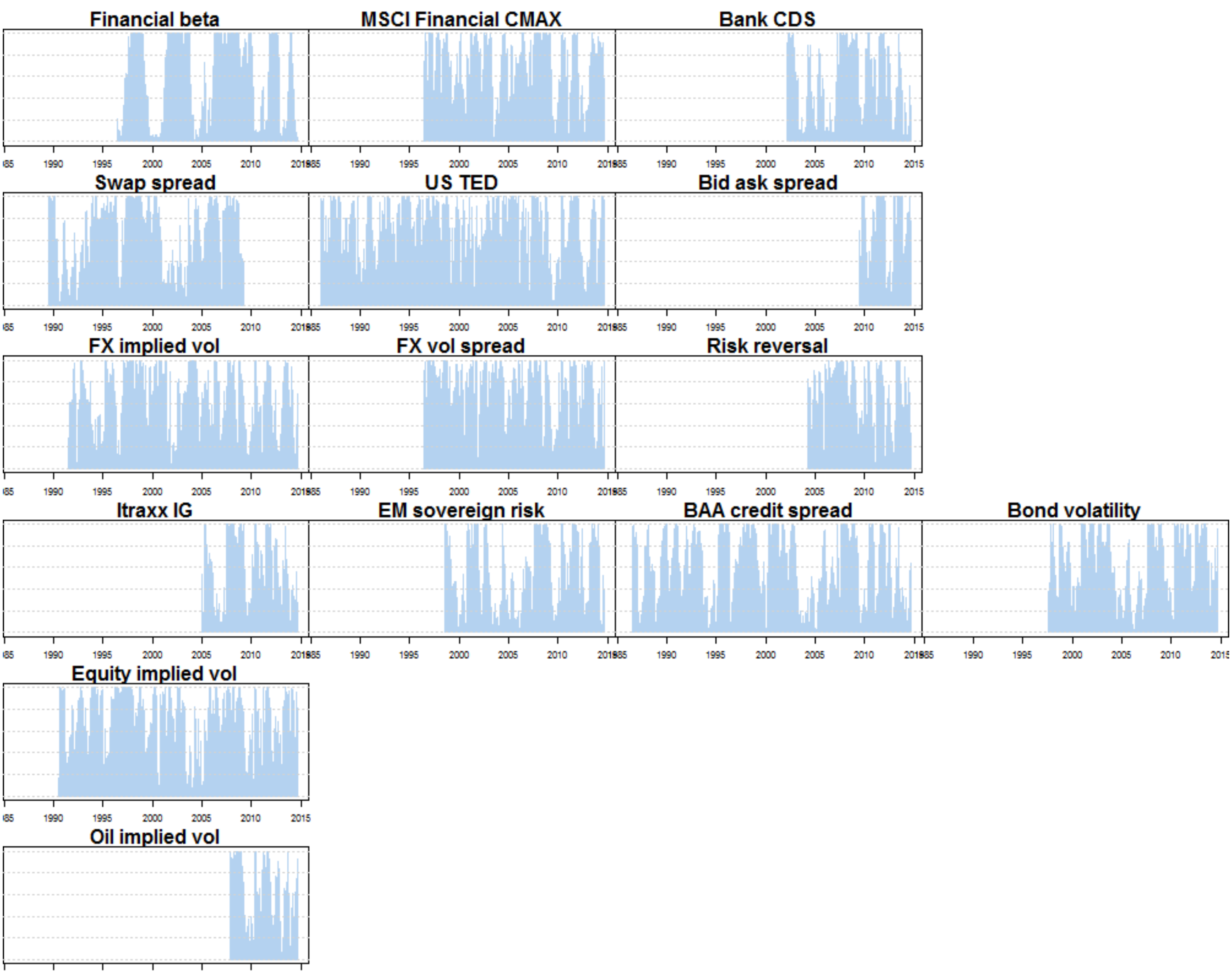


Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

How do our normalized risk proxies vary over time?

- Financial beta is less fluctuating than other proxies. It tends to stay longer in the same period of risk-off / risk-on, and it is seldom in the middle ranges.
- The US TED spread and the BAA credit spread have the longest history. Among them, the US TED spread seems to spend more time on the risk-off levels, except during 2009 when it became relatively low.
- Risk in the Equity sector was quite low around 2003-2005, and currency risk was high.

Figure 11: Normalized risk proxies (Quantile score, rolling 250-day). Each row corresponds to proxies in the same risk aversion sector: (1) Financial sector, (2) Money market, (3) Foreign exchange market, (4) Bond market, (5) Equity market and (6). Commodity market. The y-axis goes from 0 to 1.



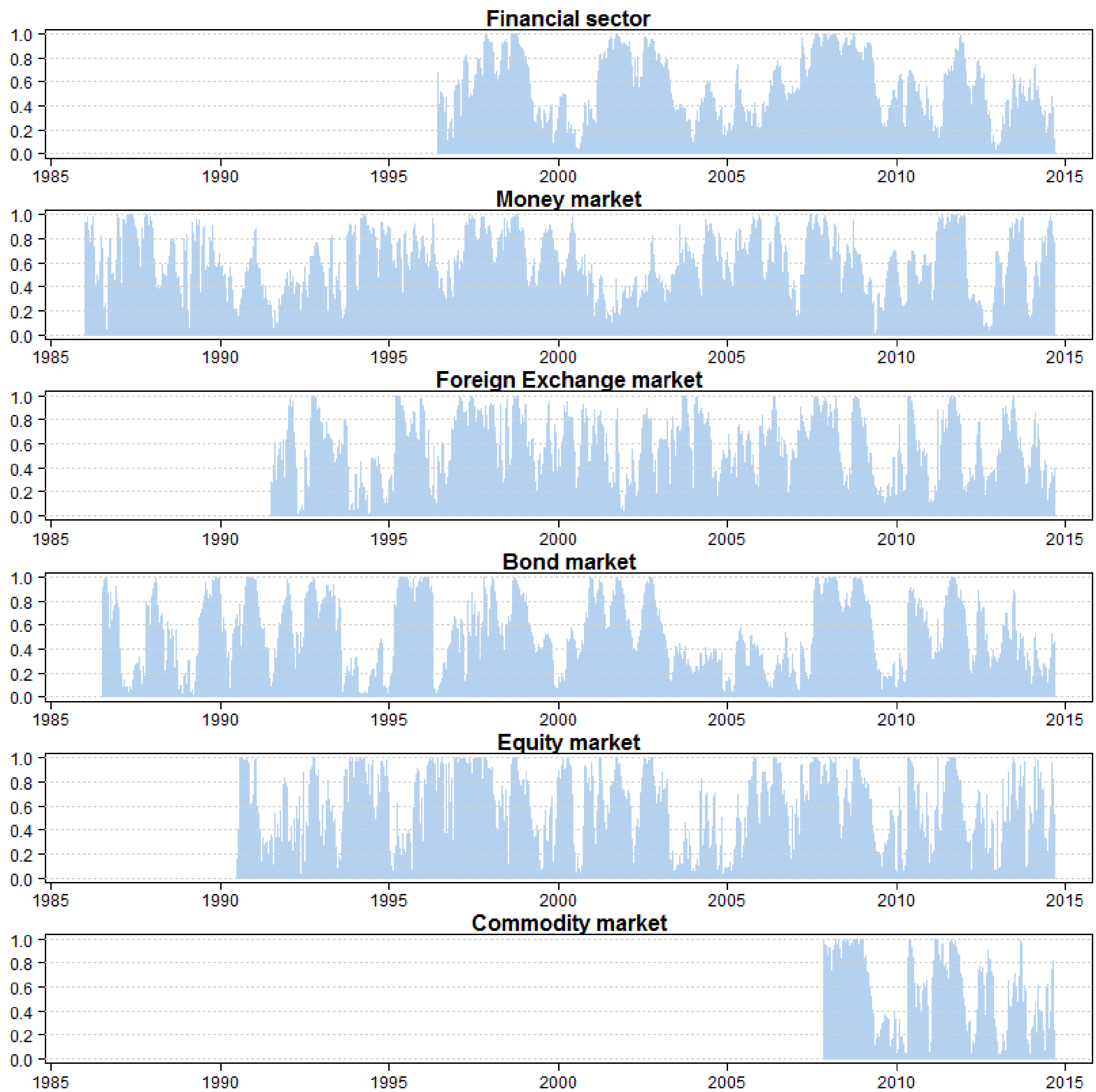
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Equal-weighting proxies within each risk aversion sector

Based on the above normalized risk proxies, we first equal weight the Quantile-scores within each group to obtain the risk in each aversion sector.

- None of the risk aversion sectors has been under recent high stress.
- Risks in the Money market, Bond market and Equity market are around their median levels.
- Risks in the Financial sector, Foreign exchange market and the Commodity market are low.

Figure 12: Time-variation of risk aversion sectors



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

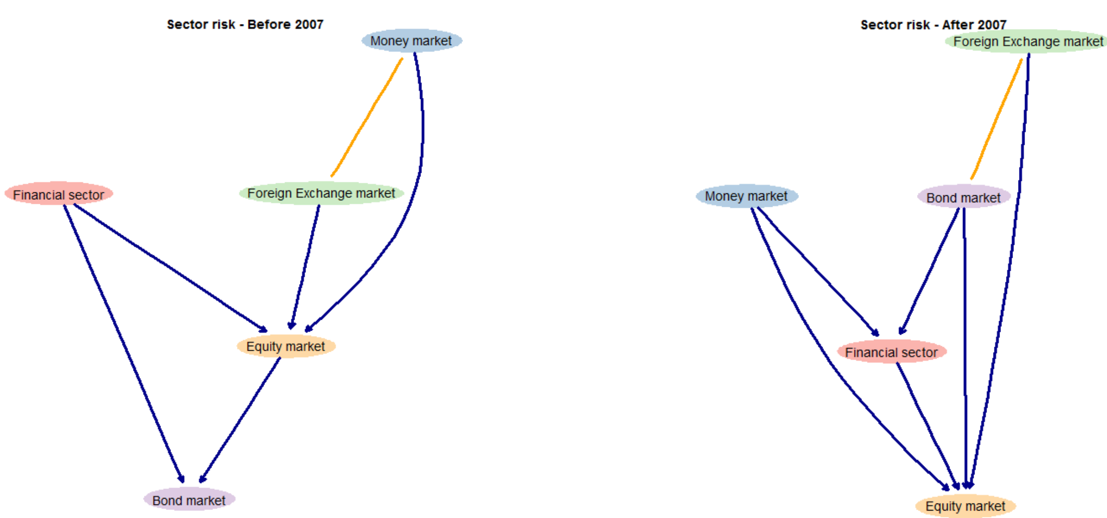
A Bayesian network of risk aversion sectors

How are sectors dependent on one another? We would like to understand how risk in one aversion sector overflows to other aversion sectors. To this end, let us start with contemporaneous dependencies. We have estimated a Bayesian network of risk aversion sectors to help visualize those dependencies. Bayesian networks have been applied quite extensively to detect causality relationships in many areas of research, e.g., to estimate drug pathways in medicine.

Since Bayesian networks are directed acyclic graphs (DAG, i.e., graphs with directed edges but no cycles), it is tempting to interpret edges as causal relations, but this is fraught with dangers. For instance, if two variables X and Y are both caused by an unobserved variable *Z*, the Bayesian network will likely have an edge $X \rightarrow Y$ or $Y \rightarrow X$. Indeed, given information about X (or Y), one can deduce some information about Y (or X). However, it is not a causal relation, but just an association since it can go either way. In particular, the direction of some edges is not well-determined (they will appear in orange in the plots below)[3].

Inferring causal relations from observational data alone has always been controversial. Intervention studies are the least controversial approach. For instance, in an experimental set-up, one can observe the variables with and without intervention and conclude that the differences observed were caused by that intervention. With financial markets, we have no way to do such experiments and manipulate the variables. Bayesian networks can help uncover patterns in the data, but care should be taken since what looks like a causal relation may just be a non-causal dependence[4].

Figure 13: Bayesian networks of risk aversion sectors: Before and after 2007



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

[3] The construction of the Bayesian network depends on conditional independence tests among variables (e.g., partial correlation tests), and introducing more variables into the network could affect the results.
[4] For more details on Bayesian networks, please refer to the Appendix. Scutari (2010) provides background on the R package (bnlearn) for estimating Bayesian networks. Other useful materials include Heckerman (1996), Ben-Gal I. (2007) and Sachs et al (2005).

Figure 13 shows the Bayesian network before and after 2007[5]. Before 2007:

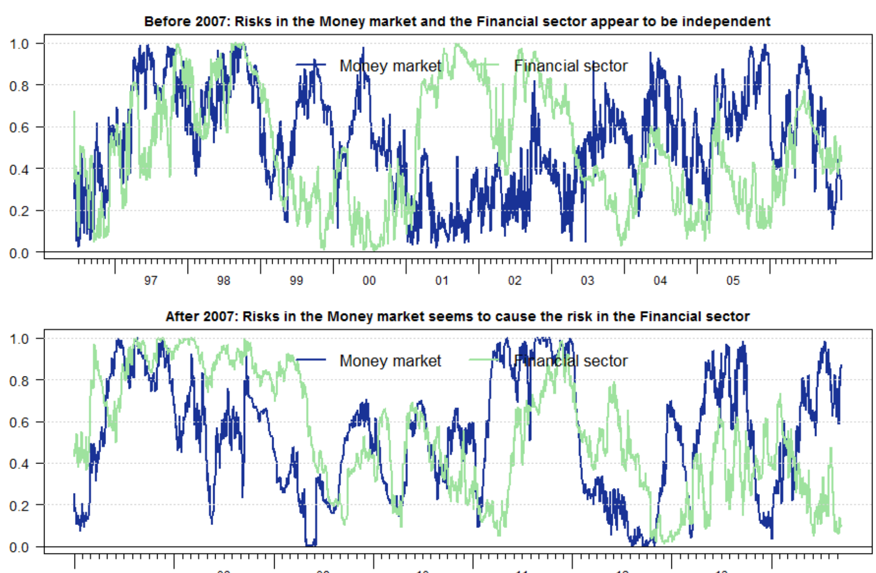
- Risks in the financial sector and the money market affect other risk aversion sectors.
- The money market and the foreign exchange market are dependent on each other, but we do not observe a clear causal direction.
- The bond market is at the bottom of the network. Its distribution depends on the risks in other risk aversion sectors, especially the financial sector and the equity market.

After 2007, changes in the hierarchy of risk aversion sectors can be observed:

- Risks in the bond market now appear to cause the risks in the financial sector and the equity market: that is the opposite of the pre-2007 situation.
- The money market is no longer independent from the financial sector, but impacts it.
- The distribution of risk in the equity market now depends on the distributions of all other risk aversion sectors.

After a closer look at what happened in the money market and the financial sector before and after 2007, the relationships unveiled from the Bayesian networks seem to make sense.

Figure 14: Correlations between the Money market and the Financial market were close to zero before 2007, but have increased to about 0.2 after the Global Financial Crisis



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

[5] We do not include the Commodity market since it does not have data before 2007.

Do risks spillover across aversion sectors?

Apart from looking at the contemporary dependencies between risk aversion sectors, we also want to understand their lead / lag relationships. Do risks propagate across sectors?

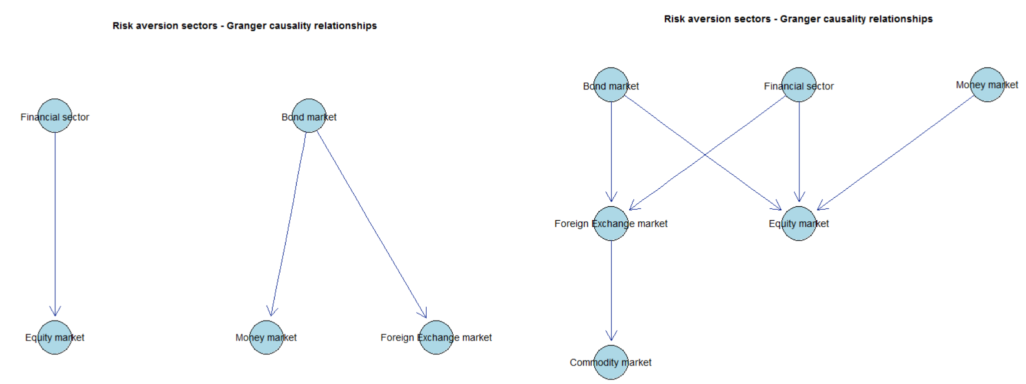
To get more insight, we perform pairwise Granger-causality tests on the risk aversion sectors to see if past information of *X* helps to predict *Y*; the Granger test uses a vector autoregressive (VAR) model, so the of *Y* is also accounted for[6]. The following directed graph displays the lead / lag relationships between our risk aversion sectors. Before 2007,

- As in the Bayesian network, past information in the Financial sector helps to explain future risk in the Equity market.
- Risks in the Bond market appear to spillover to risks in the Money market and the Foreign Exchange market.

After 2007,

- We observe more spillovers between the risk aversion sectors.
- Risks in the Money market are no longer affected by Bond market risks, and they now help to predict risks in the Equity market.

Figure 15: Lead / Lag relationships between risk aversion sectors before 2007 (left) and after 2007 (right)



Before 2007

	Money market	Foreign Exchange market	Bond market	Equity market
Money market		0.518	0.847	0.114
Foreign Exchange market	0.033		0.014	0.058
Bond market	0.000	0.002		0.913
Equity market	0.013	0.483	0.042	

After 2007

	Financial sector	Money market	Foreign Exchange market	Bond market	Equity market	Commodity market
Financial sector		0.090	0.000	0.011	0.000	0.224
Money market	0.058		0.055	0.082	0.004	0.032
Foreign Exchange market	0.086	0.204		0.083	0.000	0.005
Bond market	0.251	0.908	0.000		0.000	0.050
Equity market	0.094	0.234	0.000	0.149		0.007
Commodity market	0.139	0.352	0.162	0.098	0.009	

Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

[6] For more details on the Granger-causality test, please refer to the Appendix.

Our risk aversion indicator

How should we weight the risk aversion sectors?

With the 6 risk aversion sectors, can we combine the information into a single risk aversion indicator? There are a number of possible approaches:

Equal weighting

This is the simplest approach, which tends to work well when we are considering a very large number of proxies. For example, Guilleminot et al. (2014) applies an equal weighting approach across more than 10 risk aversion sectors.

First principal component

If we want to allocate the weights more dynamically, we can consider using the first principal component (PC). Our FX strategist has applied the first PC to construct a sentiment indicator for monitoring risk (Chen and Natividade, 2012). Hollo et al. (2012) considers a similar methodology using the cross-correlations of the components.

However, there is a potential issue when one applies the principal component approach with negatively correlated risk proxies. In that case, weighting the proxies based on their loadings on the first PC may lead to counter-intuitive results[7].

Credit weighting

This approach assesses the importance of a risk aversion sector based on dollar flows through the sectors. This is appealing since there is an intuitive economic rationale: the more credit is flowing through the sector, the larger the impact that sector has on the financial system. The Cleveland Financial Stress Index (Oet et al. 2011) and the Canadian Financial Stress Index (Illing and Liu 2006) applies such a weighting scheme. We do not consider this approach as we do not have data on credit shares.

Non-negative matrix factorization

Another way to allocate the weights to the risk aversion sectors more dynamically, while avoiding the pitfall with the first principal component, is to use a constrained version of PCA, where we force the weights to be positive. This is called Non-negative Matrix Factorization (NMF)[8].

We find that the NMF approach can add value over the simple equal-weighted approach since it is more dynamic. Hence, we will apply the NMF weighting to construct our risk aversion indicator from the sectors.

[7] A simple example is that proxy A indicates high risk but proxy B indicates low risk, while A and B are negatively correlated. If B is negative, the First PC of these 2 proxies can indicate an even higher risk than that based only on proxy A, which is counter-intuitive. This issue is avoided in Chen and Natividade (2012) and Luo et al (2009) by replacing negative correlations by zero. For more details on the issue on principal components, please refer to the Appendix.

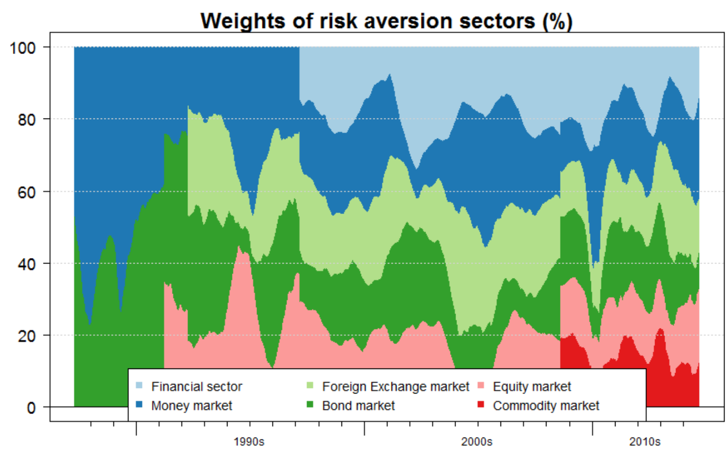
[8] For more details on the idea of NMF, please refer to the Appendix.

Importance of risk aversion sectors over time

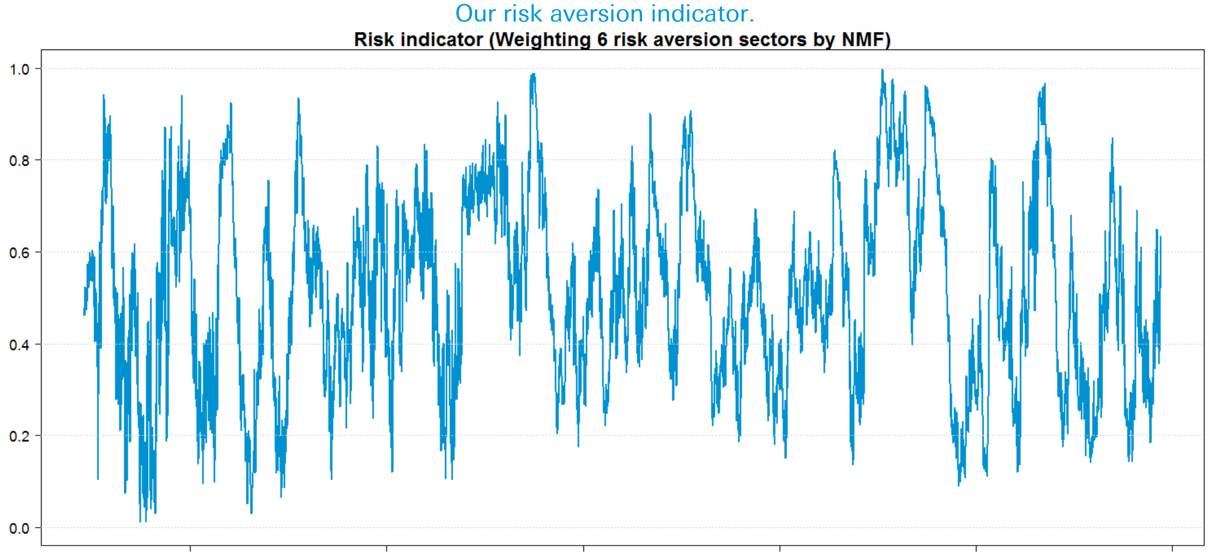
Using the approach of non-negative matrix factorization, we assign weights to each of the risk aversion sectors. The figure below shows how the importance of different sectors varies with time:

- With the Bond crisis around 1994-1995, the importance of bonds in the risk indicator also surged.
- The importance of risks in the Foreign Exchange market became much higher around 2000, probably due to the Asian currency crisis and the Russian crisis.
- Risks in the Money market have experienced a spike around 2009-2010; this could be linked to the series of post-crisis monetary measures.

Figure 16: Weighting of the risk aversion sectors based on non-negative matrix factorization



Our risk aversion indicator.



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 17: Comparison of methodologies and applications in the construction of risk indicators

	Cleveland Financial Stress Index (CFSI)	Canadian Financial Stress Index (FSI)	Composite Indicator of Systemic Stress (CISS)	Global Quantile Risk Indicator (GQRI)	Sentiment Indicator (SSI)	Risk Aversion (RA)	Our Risk Aversion Indicator
Normalization	Quantile score of each variable, based on a common set of dates with full observations of the 11 indicators	Variables are not normalized, but the final index is rebased such that it ranges from 0 to 100, with 100 being the maximum historical value of the index	Rolling quantile score	Quantile score	Quantile score	Z-score, both rolling 250-day and 125-day	Quantile score, rolling 250-day
Weights	Each indicator is identified as belonging to one of the four credit sectors (bank loans, foreign exchange credit, equity and debt). The weights are the proportion of total dollar flows through each sector in each quarter, divided by the number of indicators in the sector	Weighted by percentage shares of credit (Total credit is the sum of bank credit, corporate bonds, government bonds, equities, and USD credit)	Equal weighting within sectors, correlation-based weighting across the 5 sectors. First aggregate within sector, then aggregate as final index	First Principal Component, replacing negative correlations by zero to ensure positive weights	First Principal Component, replacing negative correlations by zero to ensure positive weights	Firstly equal weighting within sectors, then equal weighting across sectors	Non-negative matrix factorization
Applications	Use as a dependent variable for early warning system (Discussed in another paper "SAFE: An Early Warning System for Systemic Banking Risk")	This paper mainly compares different approaches in constructing the FSI (i.e. using different variables and weighting schemes). The comparison is based on Type I and Type II error, where the historical crises are based on historical survey results. It shows that the correlations between the FSI and consumer / business confidence are higher during stressful periods.	(1) Determine a systemic crisis level for Euro-area. (2) By using a threshold VAR model with 2 regimes (high and low stress), the paper shows that financial stress tends to depress real economic activity (as measured by annual growth of industrial production)	(1) Including GQRI as an exogeneous variable in the GARCH model to forecast daily volatility of AUD/USD and JPY/NZD. (2) Including GQRI as a variable in the utility function (lower when higher risk) so as to control leverage (proxied by the sum of squares of weights) in a long-only portfolio containing 3 assets (carry, value and momentum)	Compared performances of MVO, MinV and MVSK by using regime-switching models for expected returns and covariances	Strategy backtests: (1) Consider individual assets or a certain basket of assets; totally deleverage when stress is high (e.g. top quantile) (2) Consider an equal-weighted basket of assets; deleverage risky assets and only invest in safe-haven assets (Bonds) when stress is high (e.g. top quantile)	Identify risk regimes
Reference	Oet et al. (2011)	Illing and Liu (2006)	Hollo et al. (2012)	Luo et al. (2009)	Chen and Natividade (2012)	Guilleminot et al. (2014)	

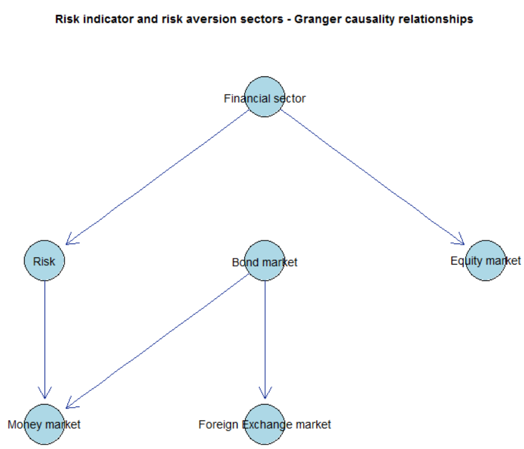
Source: Deutsche Bank Quantitative Strategy

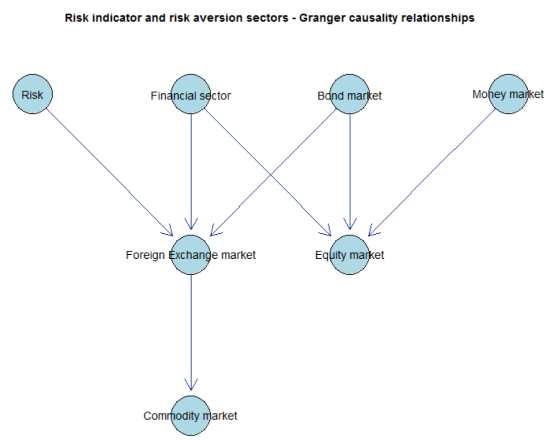
Can we predict sector risks?

An interesting question is whether our risk aversion indicator has any predictive power on future sector risks. Since our risk aversion indicator is a dynamically weighted average of the information from all the risk aversion sectors, it may help to predict future sector risks more efficiently.

- Before 2007, risks in the Financial sector help to predict our risk aversion indicator, which further helps to predict risks in the Money market.
- However, we do not see clear evidence that risks in the Financial sector help to predict risks in the Money market directly.
- After 2007, our risk aversion indicator explains future risks in the Foreign exchange market, which in turns helps to forecast risks in the Commodity market.

Figure 18: Lead / lag relationships between the risk aversion indicator and other sectors before 2007 (left) and after 2007 (right)





Before 2007: *p*-values of the Granger-causality test

	Risk	Financial sector	Money market	Foreign Exchange market	Bond market	Equity market
Risk		0.586	0.002	0.157	0.021	0.259
Financial sector	0.000		0.282	0.018	0.045	0.000
Money market	0.090	0.054		0.518	0.847	0.114
Foreign Exchange market	0.026	0.669	0.033		0.014	0.058
Bond market	0.060	0.443	0.000	0.002		0.913
Equity market	0.468	0.015	0.013	0.483	0.042	

After 2007: *p*-values of the Granger-causality test

	Risk	Financial sector	Money market	Foreign Exchange market	Bond market	Equity market	Commodity market
Risk		0.068	0.210	0.000	0.018	0.000	0.000
Financial sector	0.191		0.090	0.000	0.011	0.000	0.224
Money market	0.248	0.058		0.055	0.082	0.004	0.032
Foreign Exchange market	0.034	0.086	0.204		0.083	0.000	0.005
Bond market	0.826	0.251	0.908	0.000		0.000	0.050
Equity market	0.001	0.094	0.234	0.000	0.149		0.007
Commodity market	0.009	0.139	0.352	0.162	0.098	0.009	

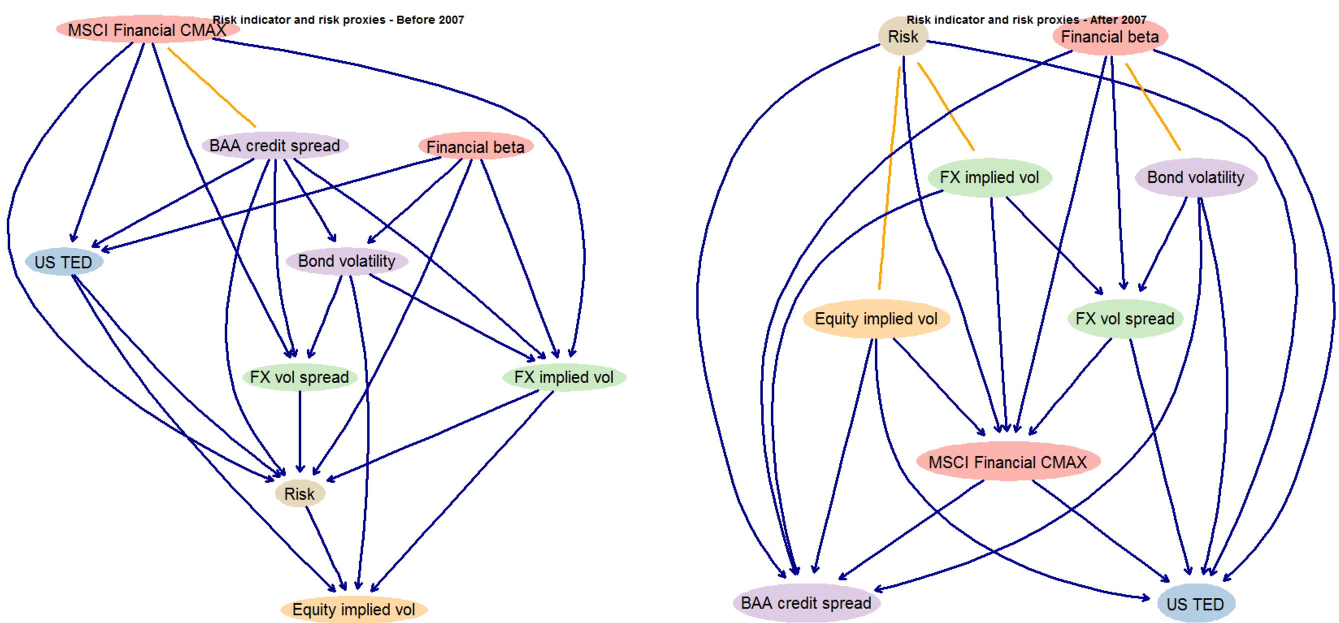
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Bayesian networks of risk aversion indicator and proxies

Of course, one can dig even deeper into the relationship between our risk aversion indicator and each of its risk proxies. Since the number of possible edges increases exponentially, it could be more difficult to disentangle the relationships among the variables. The position of our risk aversion indicator changes a lot with the Global Financial Crisis in 2007:

- Before 2007, our risk aversion indicator depends on most of the other risk proxies, e.g. US Ted spread, FX implied volatility etc.
- After 2007, our risk aversion indicator migrates much higher in the Bayesian network. It becomes the 'parent' of many other risk proxies.
- For instance, distributions in the BAA credit spread, MSCI Financial CMAX and the US Ted spread depend on our risk aversion indicator.

Figure 19: Bayesian network of risk aversion indicator and risk proxies before 2007 (left) and after 2007 (right). Risk proxies that are in the same aversion sector have the same color.

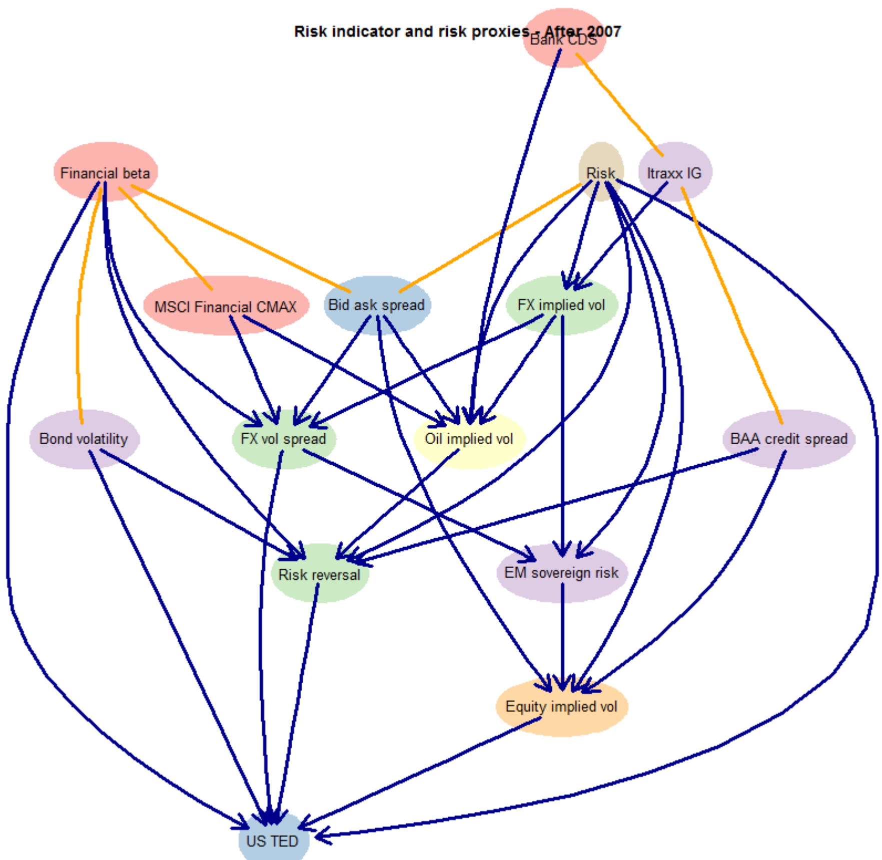


Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

The following Bayesian network includes all risk proxies that are currently available. For the bid-ask spread, we have observations since 2010.

- Interestingly, we continue to observe that risks in the Financial sector (in pink) occupy a high position the Bayesian network.
- Our risk indicator causes the risks in all other risk aversion sectors, except the Financial sector.

Figure 20: Bayesian network of risk aversion indicator and all risk proxies



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Does our risk aversion indicator lead any risk proxies?

In the previous sections, we have analyzed the predictive power of our risk aversion indicator on the risk proxies. It seemed to lead the money market before 2007, and the Foreign exchange market after.

Is it possible to observe this relationship down to the individual risk proxies? Repeating the pairwise Granger-causality test, we observe the following:

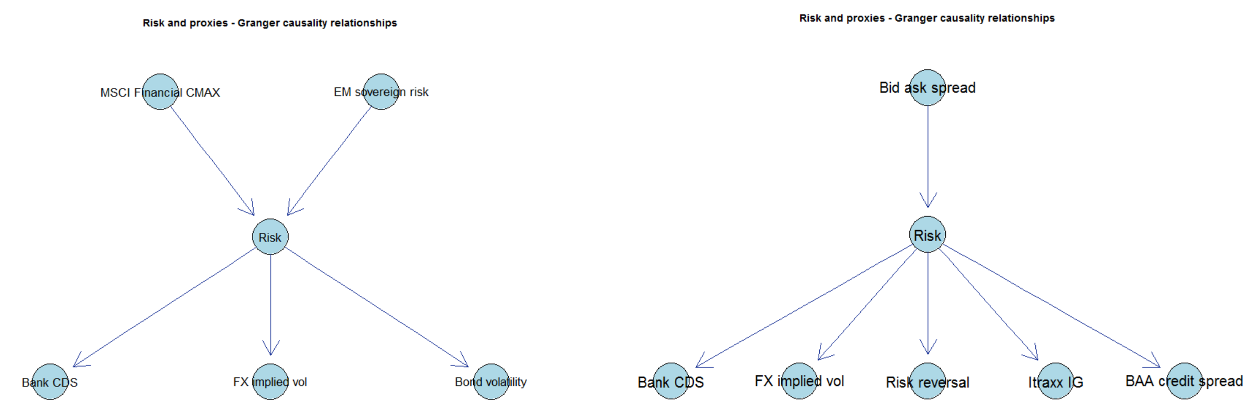
Before 2007:

- MSCI Financial CMAX and the EM sovereign risks are the proxies that add value in forecasting our risk aversion indicator.
- Our risk aversion indicator helps to predict the spread of banks' CDS, FX implied vol and bond volatility.

After 2007:

- Bid-ask spread, with a relatively short history since 2010, seems to have predictive power on our risk aversion indicator.
- As before, our risk aversion indicator helps to predict the spread of banks' CDS and FX implied vol. In addition, it helps to predict proxies in the Bond market, Itraxx IG and BAA credit spread.

Figure 21: Granger-causality graphs before 2007 (left) and after 2007 (right)



Before 2007: p-values of the pairwise Granger-causality tests

	Financial beta	MSCI Financial CMAX	Bank CDS	Swap spread	US TED	FX implied vol	FX vol spread	Risk reversal	Itraxx IG	EM sovereign risk	BAA credit spread	Bond volatility	Equity implied vol
Risk ->Proxies	0.478	0.802	0.000	0.079	0.002	0.00	0.012	0.209	0.909	0.143	0.015	0.000	0.275
Proxies ->Risk	0.538	0.000	0.421	0.320	0.009	0.02	0.156	0.886	0.206	0.000	0.032	0.373	0.436

After 2007: p-values of the pairwise Granger-causality tests

	Financial beta	MSCI Financial CMAX	Bank CDS	Swap spread	US TED	Bid ask spread	FX implied vol	FX vol spread	Risk reversal	Itraxx IG	EM sovereign risk	BAA credit spread	Bond volatility	Equity implied vol	Oil implied vol
Risk ->Proxies	0.367	0.263	0.000	1.000	0.027	0.391	0.000	0.000	0.000	0.006	0.067	0.000	0.012	0.000	0.000
Proxies ->Risk	0.494	0.692	0.267	0.247	0.095	0.003	0.021	0.002	0.151	0.293	0.018	0.667	0.187	0.002	0.005

Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Using our risk aversion indicator to zoom onto historical crises

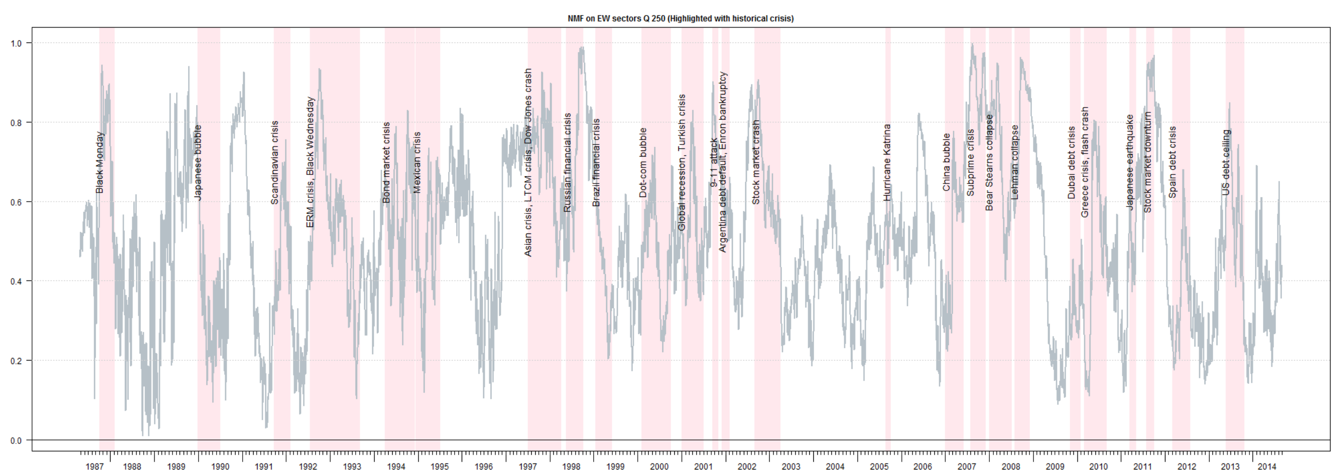
Looking back on the past few decades, we can see various financial shocks and, with perfect hindsight, we can assign approximate start and end dates to each of them. How did our risk aversion indicator change as the markets were weathering those crises? Could it indicate the current market state, or even foretell looming crises?

We have collected a comprehensive table for past crises,[9] from various sources.[10] In many cases, it is very difficult to define the end of a crisis since its impact can last for years.

In this report, the risk-off periods we consider last for 1 to 5 months. This gives a good balance of risk-off / risk-on regimes and allows us to analyze the impact of risk on asset returns.

- Our risk aversion indicator remained high during most of the important episodes of crises in the financial market, e.g. Black Monday (1987), Black Wednesday in the ERM crisis (1992), the Asian crisis (1997), Subprime crisis (2007), the Lehman collapse (2008) and the Global stock market downturn (2011).
- Since our risk proxies are global, regional risks are not always captured well. For instance, during the Dubai debt crisis (2009) and the Spain debt crisis (2012), our risk aversion indicator did not surge to a very high level.
- Crises that are due to non-financial causes are difficult to capture, and their impact tends to be shorter (e.g. 9-11 attack, Japanese earthquake in 2011).

Figure 22: Our risk aversion indicator, with historical crisis periods highlighted in pink.



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

[9] For a full list of our historical crisis, please refer to the Appendix

[10] E.g. the key dates of financial crisis from ECB: https://www.ecb.europa.eu/ecb/html/crisis.en.html

Does our risk aversion indicator react with crises?

Do we observe a significant increase in our risk aversion indicator around historical crises? To quantify the increase, we consider the changes in the average level of our risk aversion indicator 30 days before and after a crisis.

Figure 23 compares the reaction to a crisis for 5 of our risk aversion indicators, based on different aggregating and normalizing approaches.

- The EW Z risk indicator is the most reactive to the historical crisis events, but it also seems to be too noisy and to react in the opposite direction in some of the crises, such as the Brazil financial crisis, the Argentina debt crisis and the 2002 stock market crash.
- There were no reactions during the Asian crisis, Subprime crisis and Bear Stearns collapse because the risk aversion indicators were already high – in those cases, the situation had been worsening for some time, so there were no big differences in the 1-month window.

Figure 23: Change in the mean level of our risk aversion indicator over various crises; rises exceeding 20% in blue, drops exceeding 20% in pink. We have repeated the analysis with a 3-month window, and the results were similar.

	EW Z	EW Q	EW P	NMF Q	NMF P
Black Monday	+	+	+	+	+
Japanese bubble	-	-	-	-	-
Scandinavian crisis	+	+	+		+
ERM crisis, Black Wednesday	+	+	+	+	+
Bond market crisis	+			+	+
Mexican crisis	-		-	-	-
Asian crisis, LTCM crisis, Dow Jones crash					
Russian financial crisis	+	+	+	+	+
Brazil financial crisis	-				
Dot-com bubble	+				
Global recession, Turkish crisis	+	+	+	+	+
9-11 attack	+	+	+	+	+
Argentina debt default, Enron bankruptcy	-				
Stock market crash	-				
Hurricane Katrina	+		+		
China bubble	+	+	+	+	+
Subprime crisis					
Bear Stearns collapse					
Lehman collapse	+	+	+	+	+
Dubai debt crisis					
Greece crisis, flash crash	+	+	+	+	+
Japanese earthquake	+	+	+	+	+
Stock market downturn	+	+	+	+	+
Spain debt crisis	+	+	+	+	+
US debt ceiling	+	+	+	+	+
Number of positive reactions	16	13	14	13	14

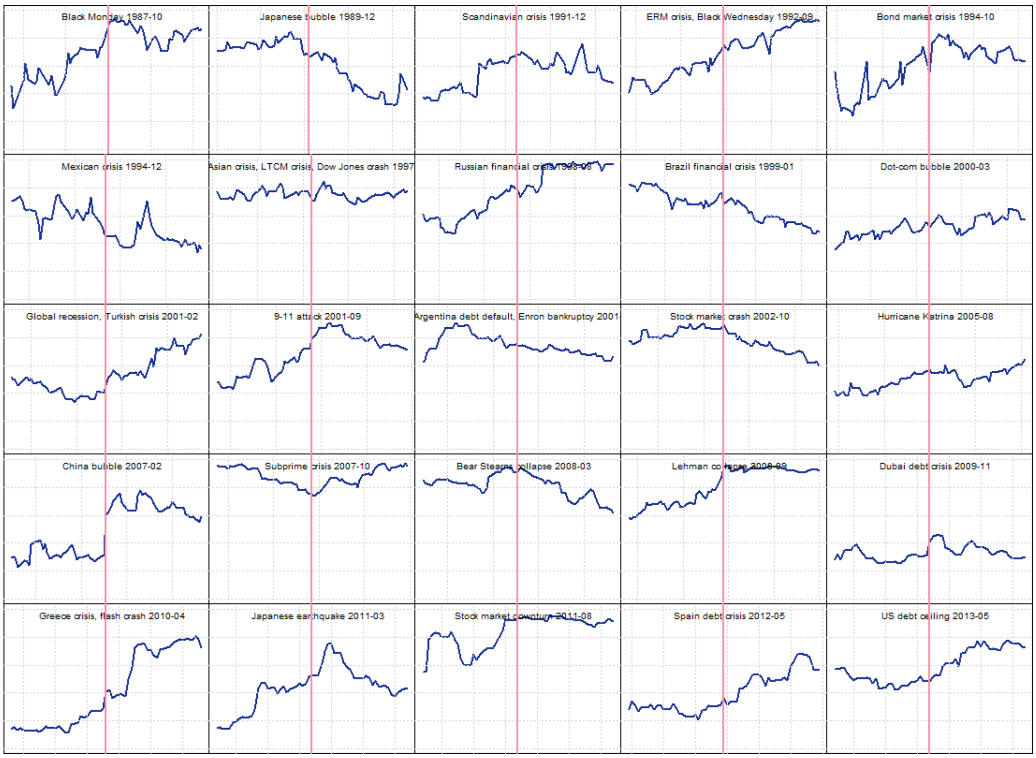
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Evolution over crisis periods

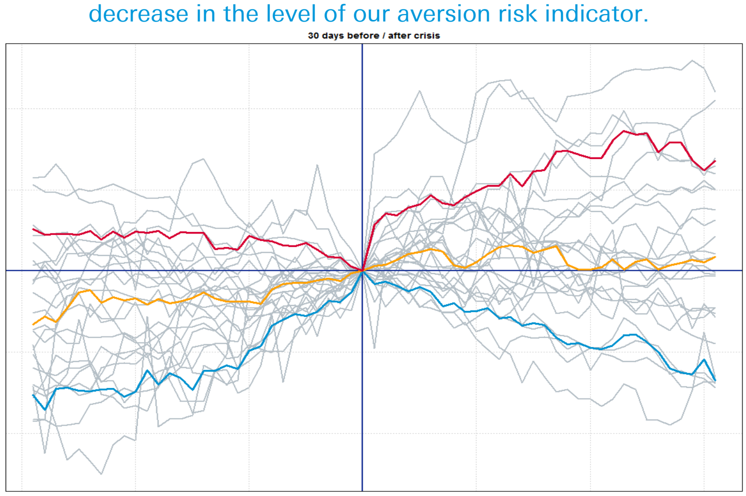
Figure 24 shows the evolution of our risk aversion indicator during crises.

By plotting all trajectories on the same graph, we can see that the levels are in general higher post-crisis.

Figure 24: Evolution of our risk aversion indicator 1 month before and after crisis. The y-axis goes from 0 to 1.



To see if our risk aversion indicator increases after a crisis in general, we plot all the trajectories on the same graph (below). We adjust the vertical level so that it is always zero at the crisis start date.
The red, yellow and blue lines show the 10th, 50th and 90th percentiles of the levels.
From this graph, we can see that the levels are in general higher post-crisis, but in a few cases there has been a decrease in the level of our aversion risk indicator.



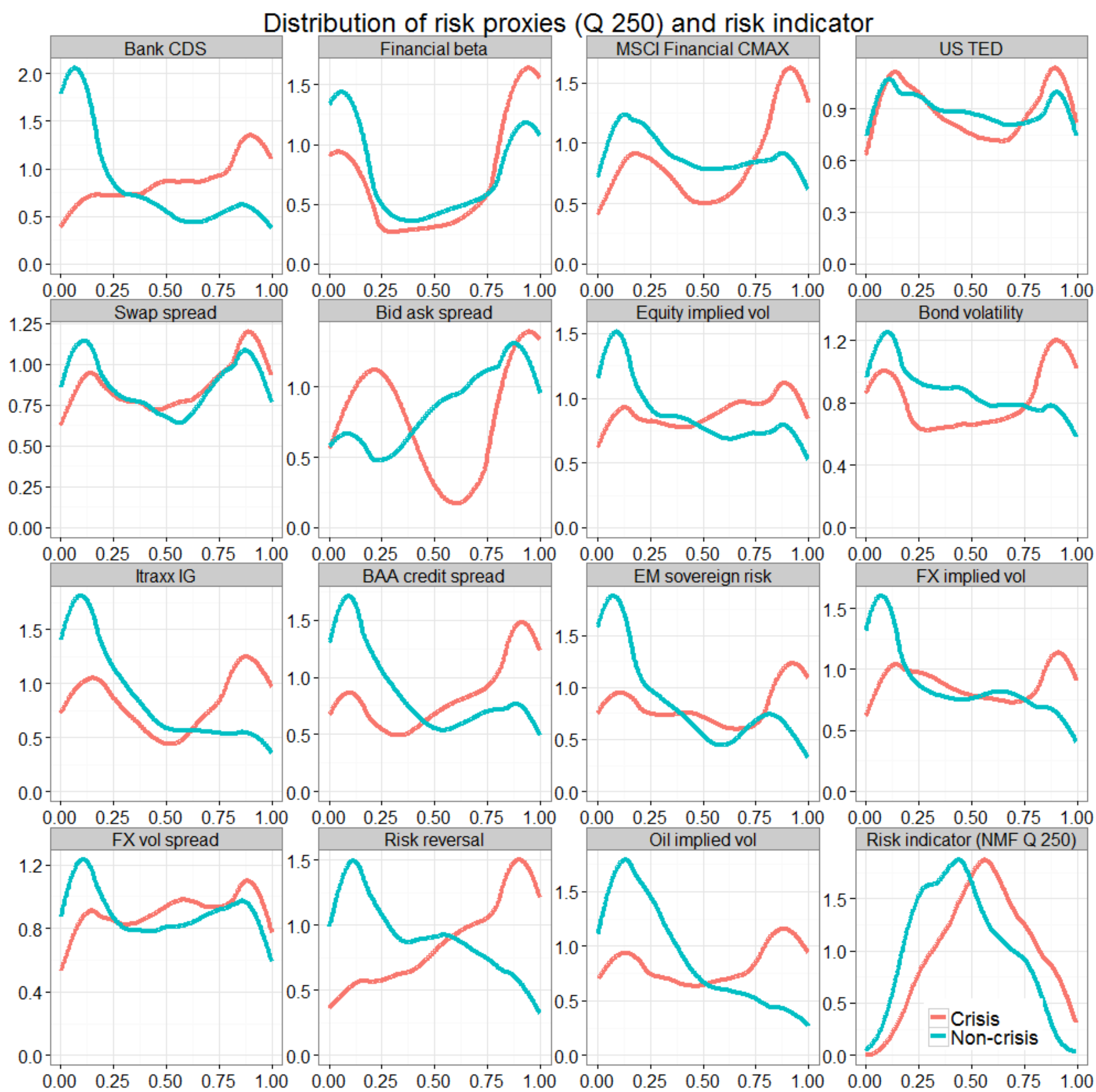
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Risk indicator distributions in different historical regimes

Here we display the distributions of the risk proxies, as well as our risk aversion indicator, during historical crisis regimes. All variables range from 0 to 1 since they are Quantile scores. Apart from the bid-ask spread, most proxies, as well as our risk aversion indicator, have a higher level during historical crises. The issue with the bid-ask spread could be due to its short history: it has only been available since 2010.

Later on, we will demonstrate that the distributions of the risk indicator are even more distinct if we consider 3 regimes (risk-off, normal and risk-on) instead of 2 regimes (crisis and non-crisis).

Figure 25: Historical distribution of our risk aversion indicator and the normalized risk proxies during crisis and non-crisis episodes



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Identifying risk regimes - How high is high?

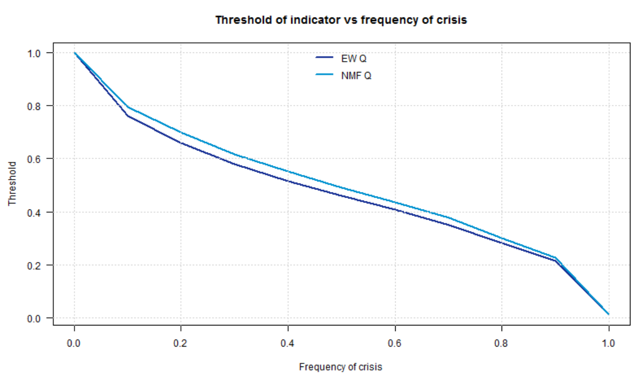
Equipped with a risk aversion indicator, we want a guideline to interpret the levels. Intuitively, higher levels of risk correspond to more stressful periods: we can choose a threshold to identify risk-off regimes. But how can we choose it? Is 0.7 high enough? Or is 0.9, which would make crises rarer and more extreme, preferable? Should we use a fixed or time-varying threshold?

Risk-off beyond some threshold

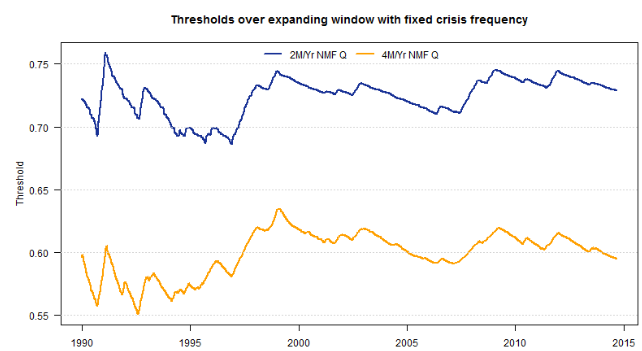
The choice of the threshold determines the frequency or crises, as shown in Figure 26.

Figure 26: The choice of the threshold implies that we have a certain frequency of crisis occurrence.

Fixed threshold versus frequency of crisis



Thresholds estimated on expanding window such that the frequency of crisis is at 2 months/year or 4 months/year.

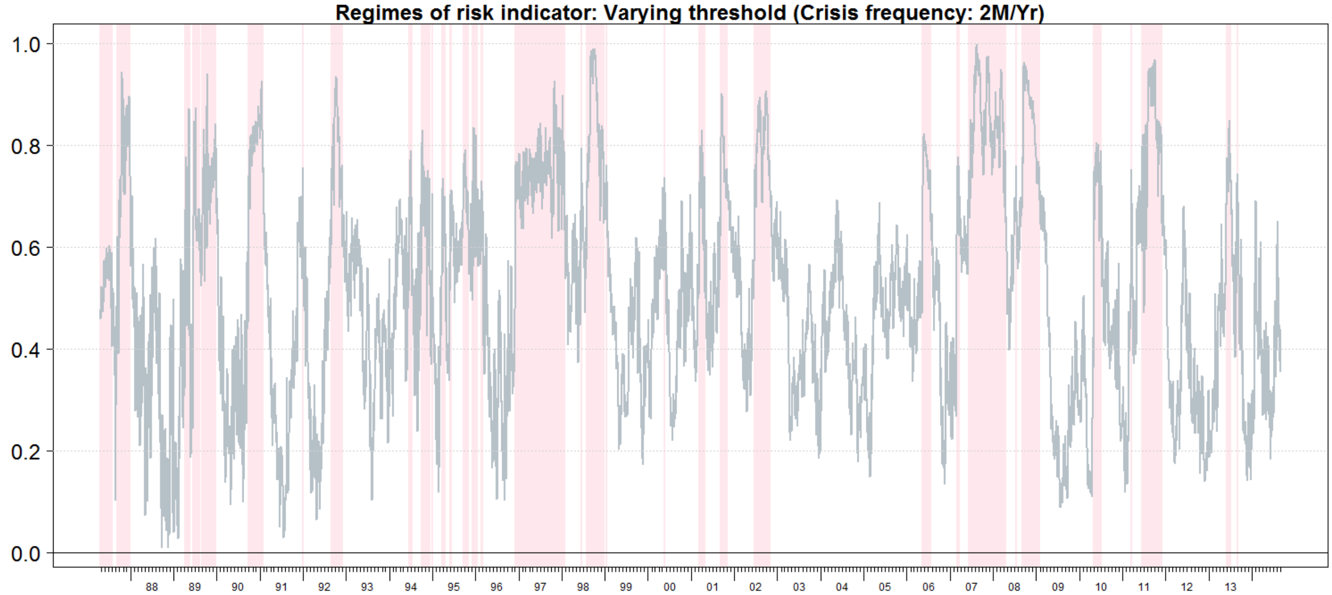


Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

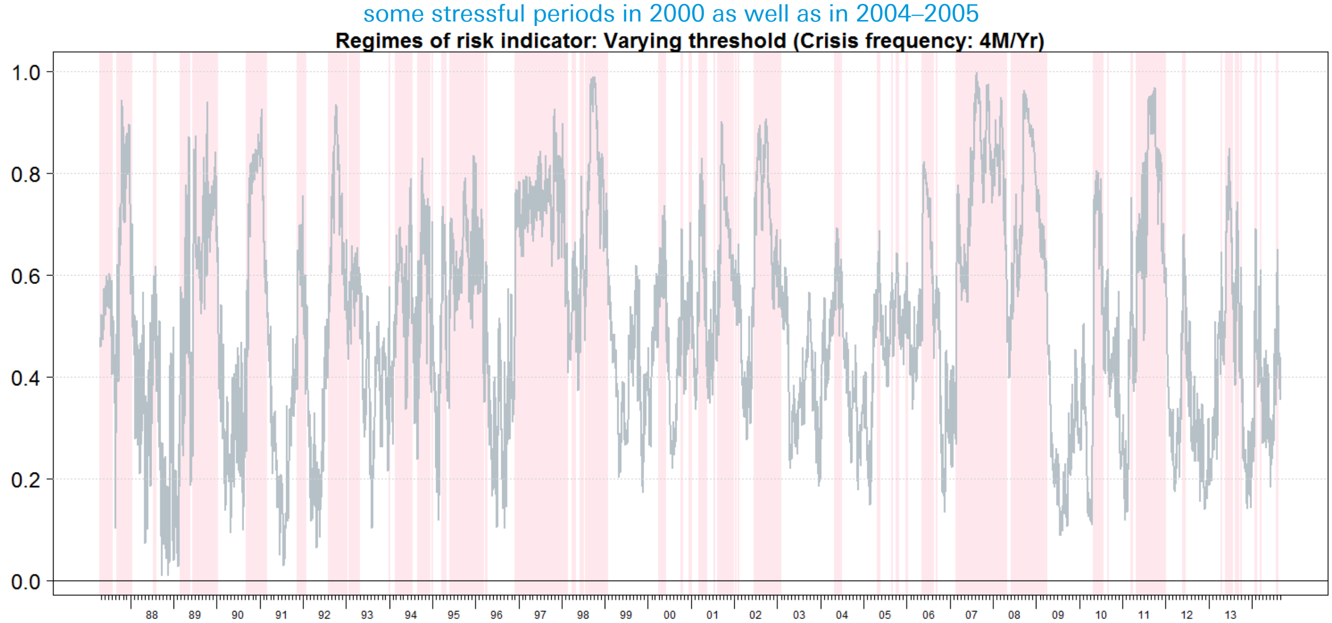
Figure 27 highlights the risk-off regimes when the risk aversion indicator exceeds a certain threshold. On the top, we set the threshold to 0.7, which corresponds to a crisis frequency of 2 months/year. At the bottom, we use a lower threshold, 0.6.

By construction, there will be more crisis episodes if we choose a lower threshold. In particular, we begin to observe some stressful periods in 2000 as well as in 2004–2005.

Figure 27: Risk-off regimes (pink) when the risk aversion indicator exceeds a certain threshold: 0.7 (top) and 0.6 (bottom).



By construction, there will be more crisis episodes if we choose a lower threshold. In particular, we begin to observe some stressful periods in 2000 as well as in 2004–2005



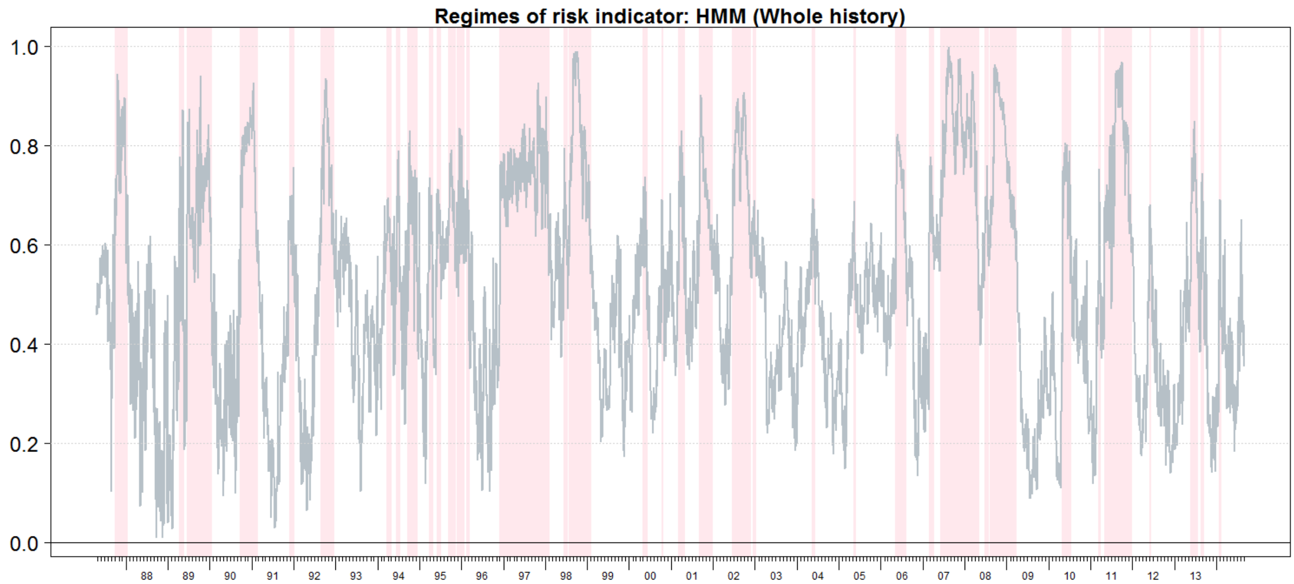
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Risk-off regimes with a Hidden Markov Model

Another way to systematically identify regimes is to estimate a regime-switching model. We fit a hidden Markov model (HMM) to our risk aversion indicator, and assume that it has different distributions in each regime[11]. The sequence of regimes is a hidden process, to be estimated. We have tested with 2 or 3 regimes, and we find that using 3 regimes provides a better fit of the data.

Using the hidden Markov model, we estimate the posterior probability of each regime. We then classify a period from that posterior probability. For instance, the figure below highlights the periods where the posterior probability exceeds 50%.

Figure 28: Risk-off regimes (pink) based on HMM, estimated over whole history



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

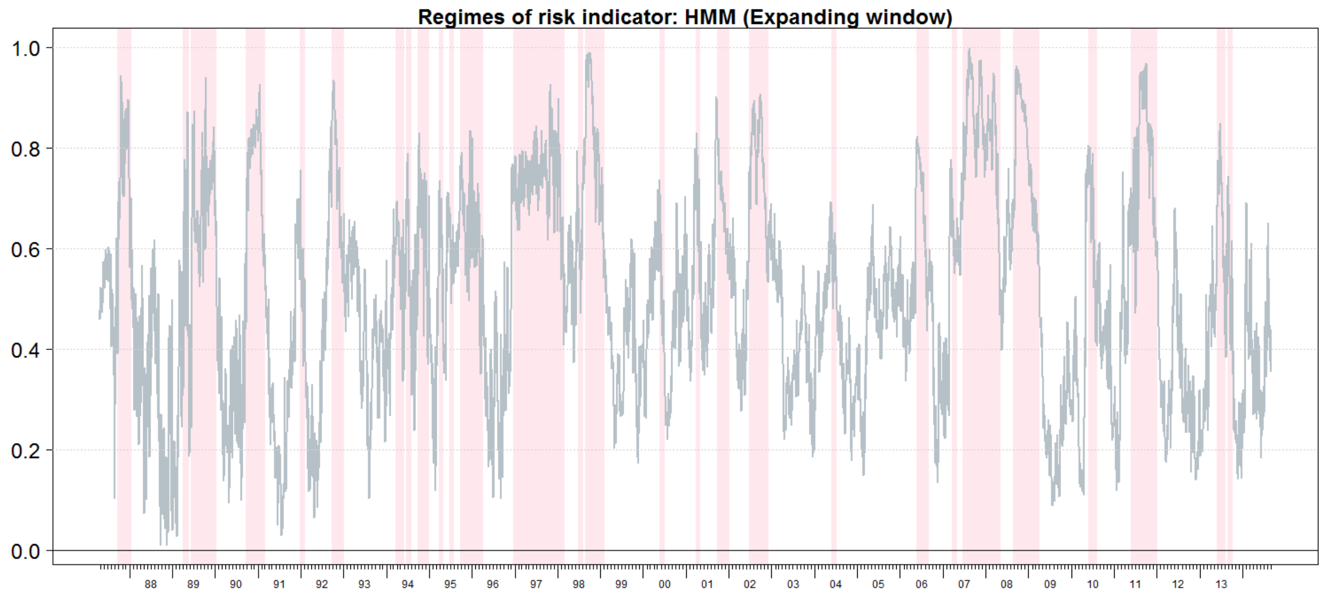
Expanding window

To prevent look-ahead bias, we use an expanding window. The figure below shows the risk-off regimes estimated at the end of each month, starting in mid 1987, to ensure we have accumulated enough observations. Since the model is estimated monthly, a regime remains the same for the whole month.

There are discrepancies between the whole history and expanding window models for about 20% of the dates. For one third of those differences, the whole-history regime is "normal" but the moving-window one is "risk-on". Those discrepancies are evenly distributed over time: there is no particular period during which the two models differ more.

[11] For more details on the hidden Markov model, please refer to the Appendix.

Figure 29: Risk-off regimes (pink) based on the HMM, estimated over expanding window.



Source: Deutsche Bank

Do we classify regimes well?

True warnings versus false alarms

The hidden Markov model outputs a time series of regimes (risk-off, normal and risk-on). To measure how well this classification works, we can look at historical crises (the "true" risk-off regimes) and compute the percentage of true warnings versus false alarms of our estimated regimes.

Area under the curve (AUC)

We will also look at the area under the ROC (receiver-operator characteristic) curve, which is a more comprehensive summary of the accuracy of our estimated regimes. Basically, it shows the levels of true warnings and false alarms when we adjust the threshold of our classification from 0 to 1. AUC is usually between 0.5 (random classifier) and 1 (perfect classifier).

Regime Classification Measure (RCM)

Another evaluation criterion is the Regime Classification Measure (RCM), also used in Hollo et al. (2012). This only applies to regimes estimated from a model (e.g. our hidden Markov model) since it depends on the posterior probabilities. The idea is that if the posterior probabilities of the regimes are always high, then we have better confidence on a certain regime. The RCM ranges from 0 (perfect confidence on the regimes) to 100 (totally ambiguous regimes). The smaller the RCM is, the better the classification of regimes are.

Evaluation over the whole history

Figure 30 shows the evaluation measures of a list of risk indicators, the normalized risk proxies, as well as the US Variance Risk Premium (VRP), which is one of our favorite risk indicators, particularly for the US markets. We also include the evaluation of the risk proxies to demonstrate the added value of our risk indicator[12].

Figure 30: Evaluation of regime identifications based on whole history

	True warnings (%)	False alarms (%)	AUC	RCM
2M/Yr Fixed	24.5	11.8		
4M/Yr Fixed	44.9	26.1		
2M/Yr Varying	25.1	14.7		
4M/Yr Varying	44.1	27.1		
EW Z	37.8	22.8	0.65	6.20
EW Q	37.5	21.6	0.64	5.82
EW P	38.0	21.9	0.64	5.79
NMF Q	39.6	22.4	0.65	5.63
NMF P	38.8	23.2	0.66	5.70
Financial beta	36.1	19.6	0.60	2.23
MSCI Financial CMAX	38.4	17.5	0.63	5.63
Bank CDS	46.5	20.0	0.74	3.38
Swap spread	30.2	24.4	0.54	5.71
US TED	30.1	24.8	0.52	8.62
Bid ask spread	50.4	36.7	0.54	2.81
FX implied vol	45.9	34.3	0.61	6.30
FX vol spread	33.4	28.8	0.56	8.16
Risk reversal	45.5	17.6	0.71	5.95
Itraxx IG	51.1	26.6	0.66	4.44
EM sovereign risk	44.7	24.6	0.66	3.29
BAA credit spread	41.2	20.0	0.66	4.64
Bond volatility	44.4	31.2	0.57	4.48
Equity implied vol	37.7	26.0	0.60	7.88
Oil implied vol	37.3	11.5	0.65	5.59
US VRP	28.7	26.3	0.50	13.10
NMF Q Expanding	39.2	23.0	0.65	5.80

Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

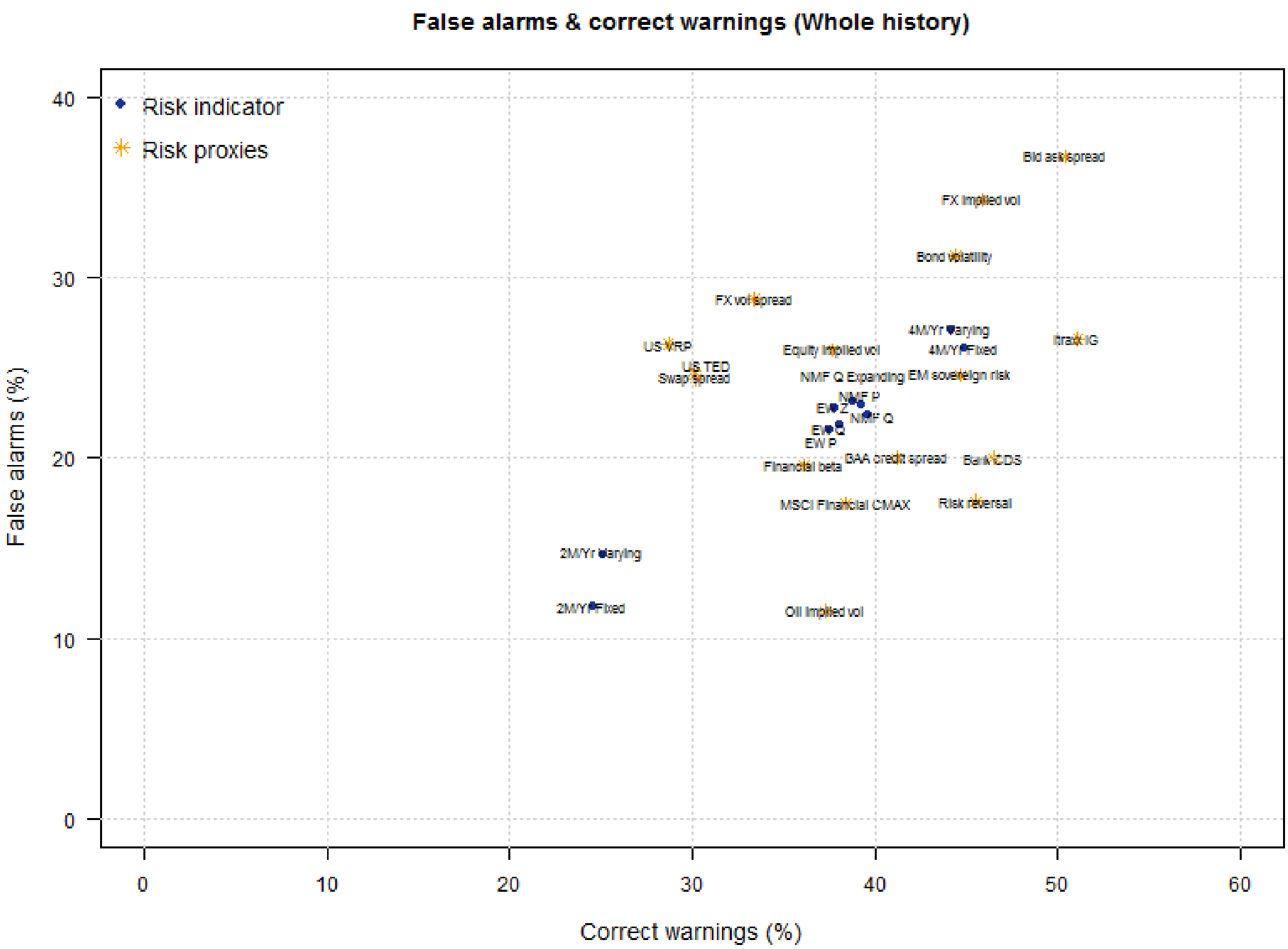
- We find that our risk indicator (NMF Q) scores quite well among the others, with a high hit rate of almost 40%, even when we estimate the regimes in an expanding window.
- The threshold-based regime classification (i.e. 2M/Yr or 4M/Yr) are defined by a prior on the crisis frequency. Assuming 4M/Yr of crisis will lead to a high hit rate, but also more false alarms.
- Comparing the NMF approach and the Equal-weight approach of constructing the risk indicators, we observe that the performance is close, with the NMF approach being slightly better at identifying true crises. We also see that equal-weighting the Z-score risk aversion sectors results in more false alarms, and a poorer RCM score.
- Among the risk proxies, the BAA credit spread and the MSCI Financial CMAX are good indicators to classify risk regimes. They have a high rate of true warnings and also a relatively low rate of false alarms[13].

[12] The regimes identified from the risk proxies (and US VRP) are estimated with the hidden Markov model using the whole history. The only 3 regimes that are estimated using an expanding window are the 2M/Yr Varying (threshold), 4M/Yr Varying (threshold) and the NMF Q Expanding ones.

[13] Bank CDS and Risk reversal also seem to perform well, but their history is much shorter: it only starts in 2004 and they may not be directly comparable with most proxies.

To visualize the evaluations, let us focus on the percentage of true warnings and false alarms among the indicators and risk proxies. The plot below shows the false alarms rate versus the true warnings rate of all the indicators. Positions closer to the bottom-right corner corresponds to indicators that, historically, were better able to identify regimes.

Figure 31: Correct warnings and false alarms based on whole history



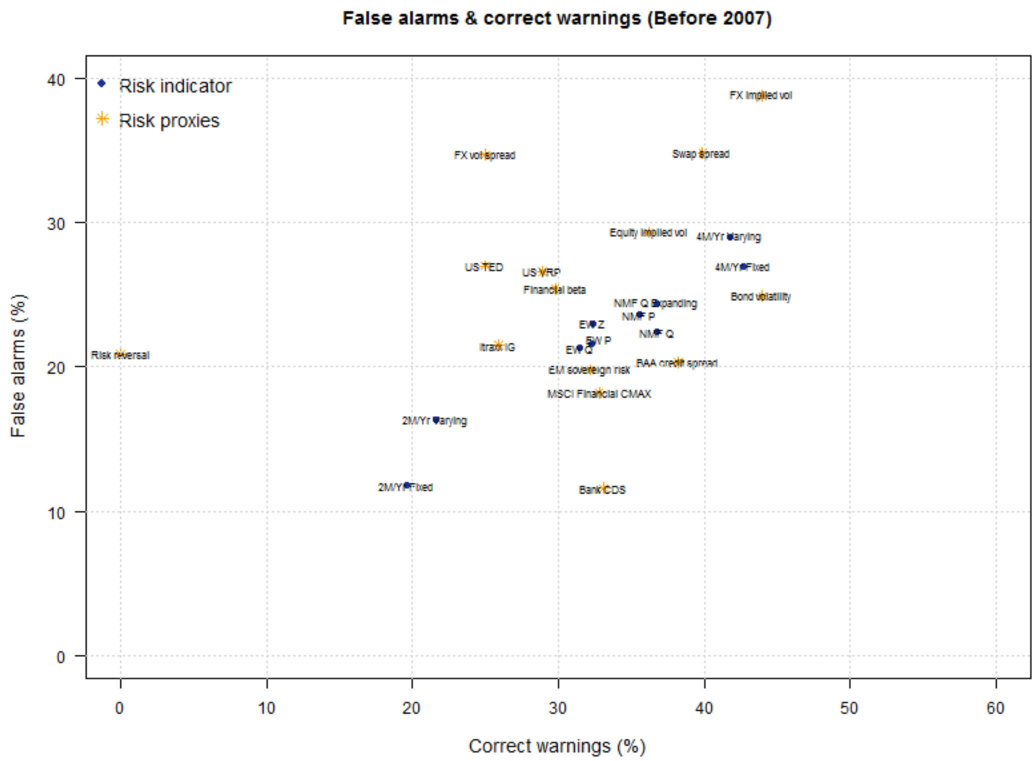
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

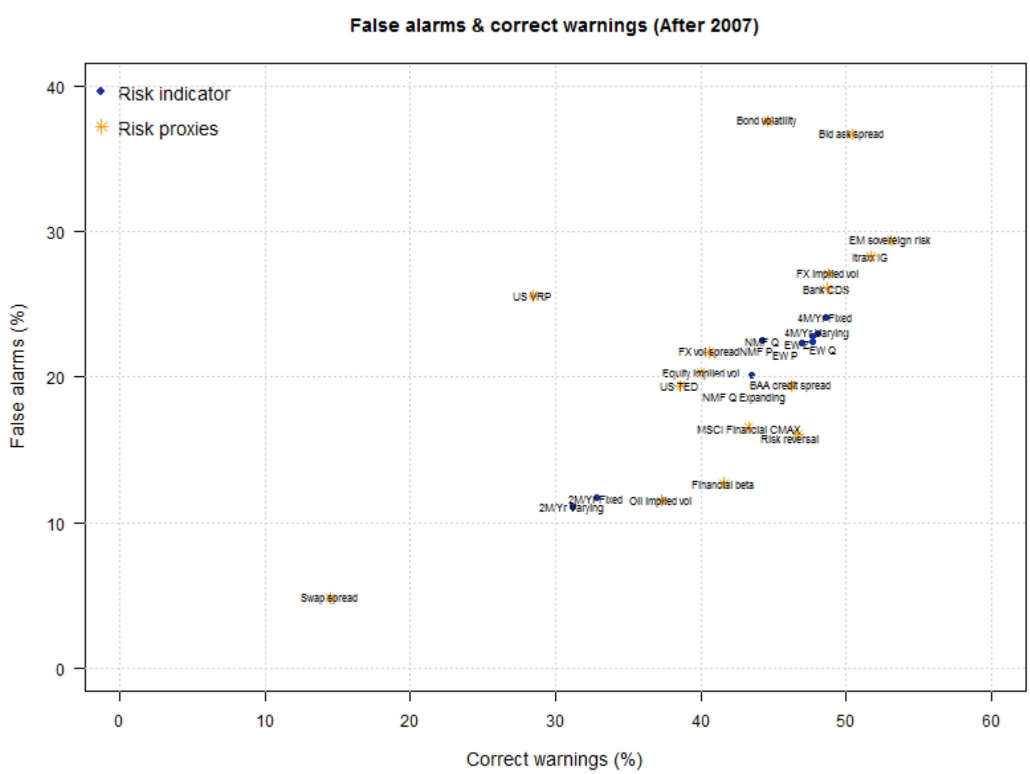
Have things changed in 2007?

To see if the performance of the indicators varies with time, we show the evaluation scores before and after 2007. Before 2007, the BAA credit spread was one of the best regime classifiers, with a slightly lower rate of false alarms than our risk aversion indicator.

After 2007, we observe significantly higher rates in both the true warnings and the false alarms. Risk reversal becomes one of the best classifiers. By aggregating all the risk proxies dynamically, our risk aversion indicator delivers stable and decent performance in identifying risk regimes.

Figure 32: Correct warnings and false alarms before 2007 (top) and after 2007 (bottom)





Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

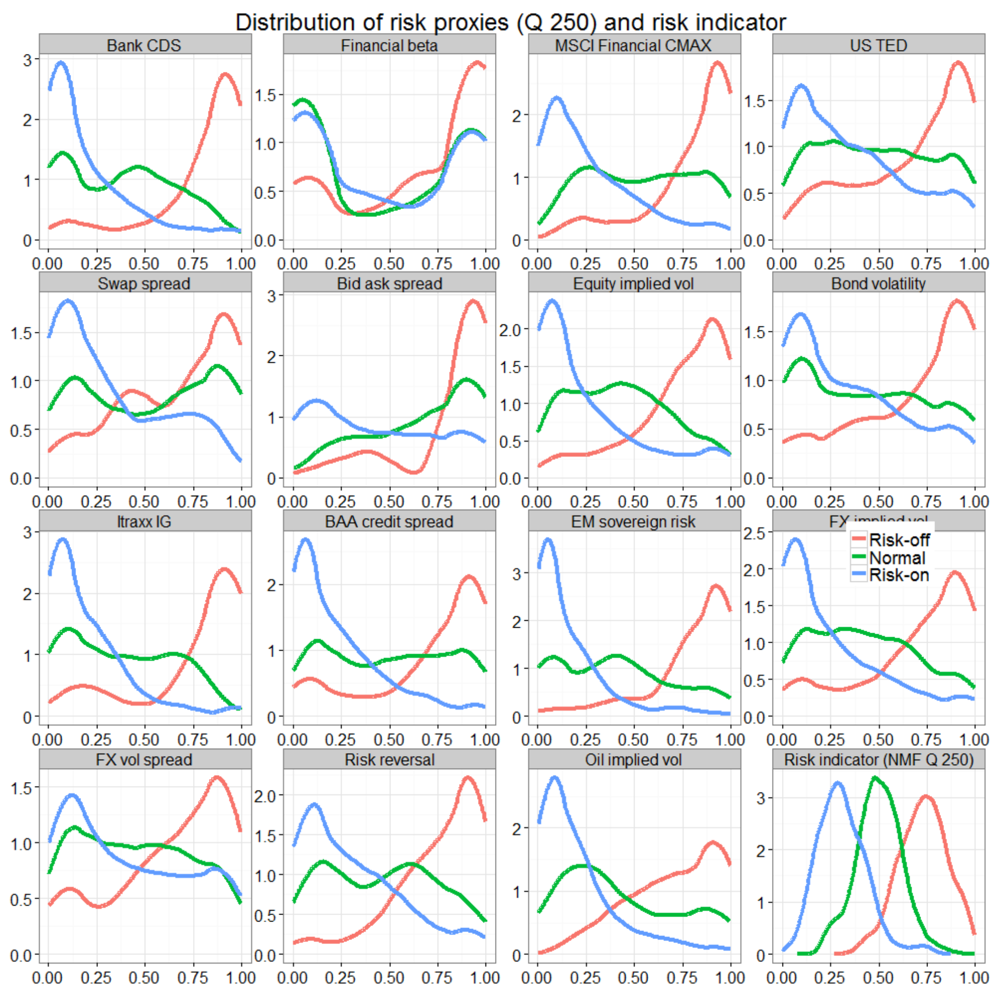
Distribution of risk aversion indicator in estimated regimes

As we see above, estimating risk regimes with a Hidden Markov Model gives good regime classifications, even when we consider an expanding estimation window. Let us now look at the distributions of the proxies and risk indicators under these estimated regimes.

Figure 33 provides a sense of the relevance of the proxies in constructing our risk indicator. By definition of the HMM, we expect a clear separation of the risk-off / normal / risk-on regimes for our risk aversion indicator.

Most of the proxies are also higher during risk-off regimes, and lower during risk-on regimes. This helps to justify that our 'ingredients' should serve as relevant proxies when it comes to identifying risks.

Figure 33: Distributions of risk proxies and risk aversion indicator in estimated regimes based on the HMM under expanding window.



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

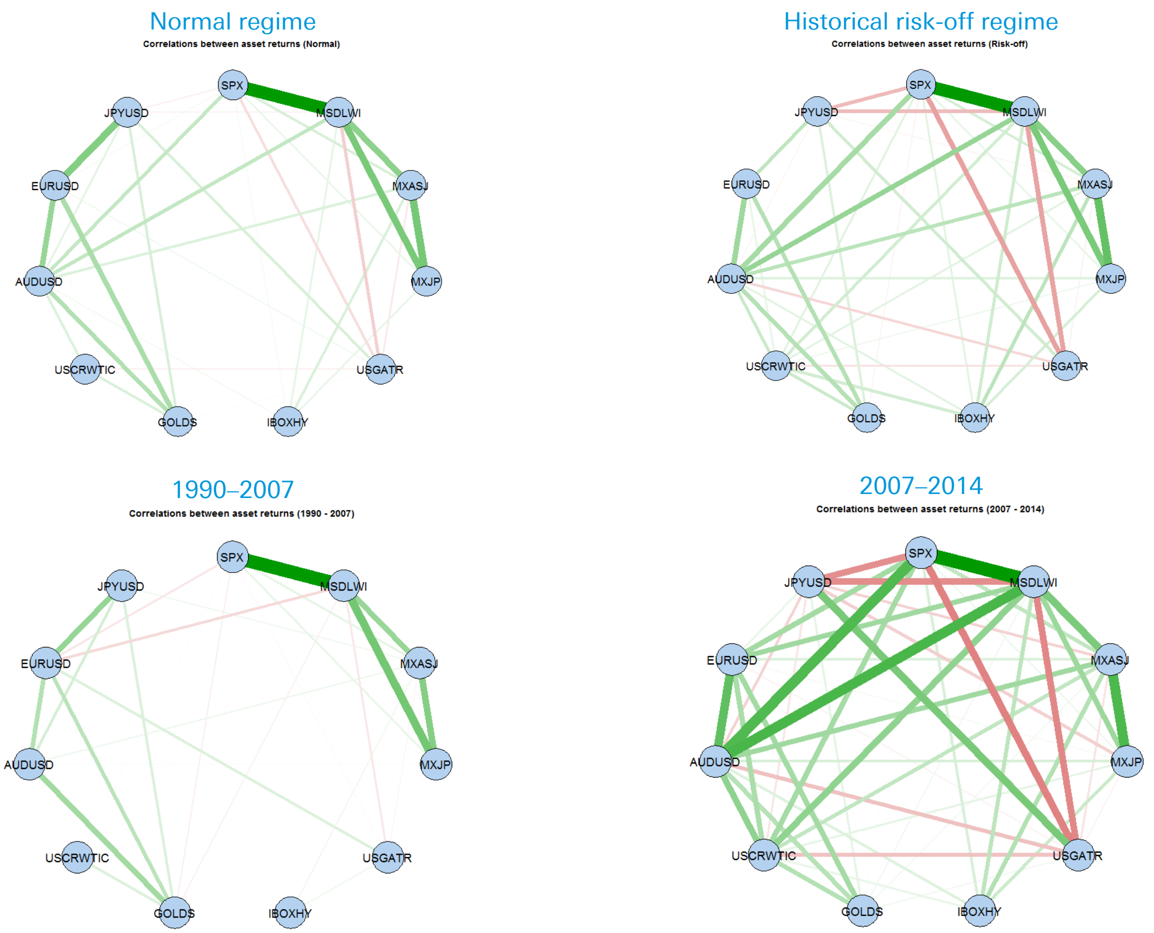
Risk and returns are inter-related…

When risk aversion is high, investors no longer want to take risks – this preference will translate into returns. What do we see about asset returns in different risk regimes?

Asset correlations

We observe that asset correlations tend to be much higher during risk-off regimes: different asset classes in the financial market collapse together. We also look at the difference before and after 2007, and find that asset correlations became much higher after the Global Financial Crisis. This indicates that the financial market has become more concentrated.

Figure 34: Correlation graphs of asset returns during different periods. Asset returns that are positively correlated are linked by green edges, and those that are negatively correlated are linked by red edges. Stronger correlations correspond to thicker edges.



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Bayesian network of risk and returns

Are there contemporary relationships between asset returns and our risk aversion indicator? As before, we use Bayesian networks, and we lag the returns in MSCI Japan and MSCI Asia ex-Japan by 1 day.

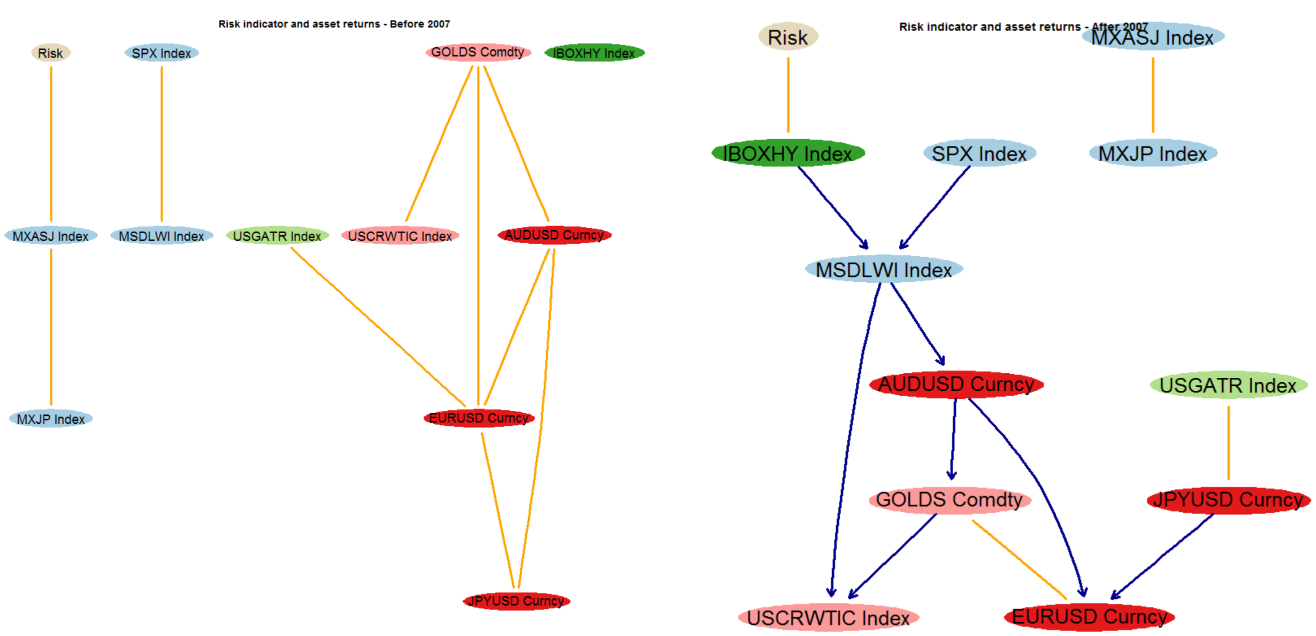
Before 2007:

- We cannot infer any causality direction among the variables. The Bayesian network only shows that there are groups of dependent variables, mainly within asset classes
- Our risk aversion indicator is dependent on the returns of MSCI Asia ex-Japan.
- Among the asset returns, MSCI Asia ex-Japan seems to be the cause of many other asset returns.
- Currencies and commodity returns are dependent on each other.

After 2007:

- We observe some causal relationships among the returns, but not with our risk aversion indicator.
- Our risk aversion indicator is dependent on high yield returns.
- S&P 500 returns affect the returns of MSCI World, which in turn affect the AUD/USD returns and the returns on oil.

Figure 35: Bayesian network of risk aversion indicator and asset returns before 2007 (left) and after 2007 (right).



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

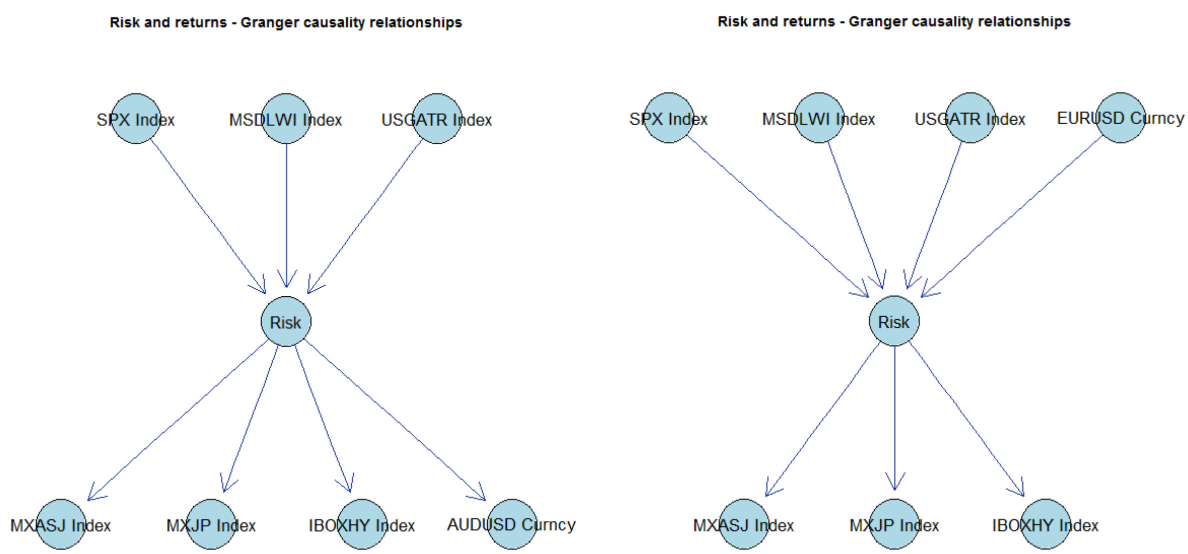
Can we predict returns with our risk aversion indicator?

Below, we simply check if our risk aversion indicator has any predictive power on asset returns using the pairwise Granger-causality tests. Again, we lag the returns in MSCI Japan and MSCI Asia ex-Japan by 1 day.

Here the relationships seem to be quite stable both before and after 2007:

- Our risk aversion indicator helps to predict high yield returns, MSCI AxJ and MSCI Japan returns;
- On the other hand, past information on S&P 500, MSCI World and US government bond shows predictive power for risk.

Figure 36: Granger causality between risk and returns before 2007 (left) and after 2007 (right)



Before 2007

	SPX Index	MSDLWI Index	MXASJ Index	MXJP Index	USGATR Index	IBOXHY Index	GOLDS Comdty	USCRWTIC Index	AUDUSD Curncy	EURUSD Curncy	JPYUSD Curncy
Risk ->Returns	0.48	0.783	0.000	0.000	0.126	0.000	0.129	0.215	0.007	0.018	0.599
Returns ->Risk	0.00	0.000	0.267	0.314	0.000	0.521	0.167	0.544	0.075	0.679	0.122

After 2007

	SPX Index	MSDLWI Index	MXASJ Index	MXJP Index	USGATR Index	IBOXHY Index	GOLDS Comdty	USCRWTIC Index	AUDUSD Curncy	EURUSD Curncy	JPYUSD Curncy
Risk ->Returns	0.029	0.216	0.000	0.000	0.741	0.000	0.705	0.264	0.772	0.831	0.186
Returns ->Risk	0.000	0.000	0.053	0.578	0.003	0.291	0.191	0.866	0.032	0.002	0.012

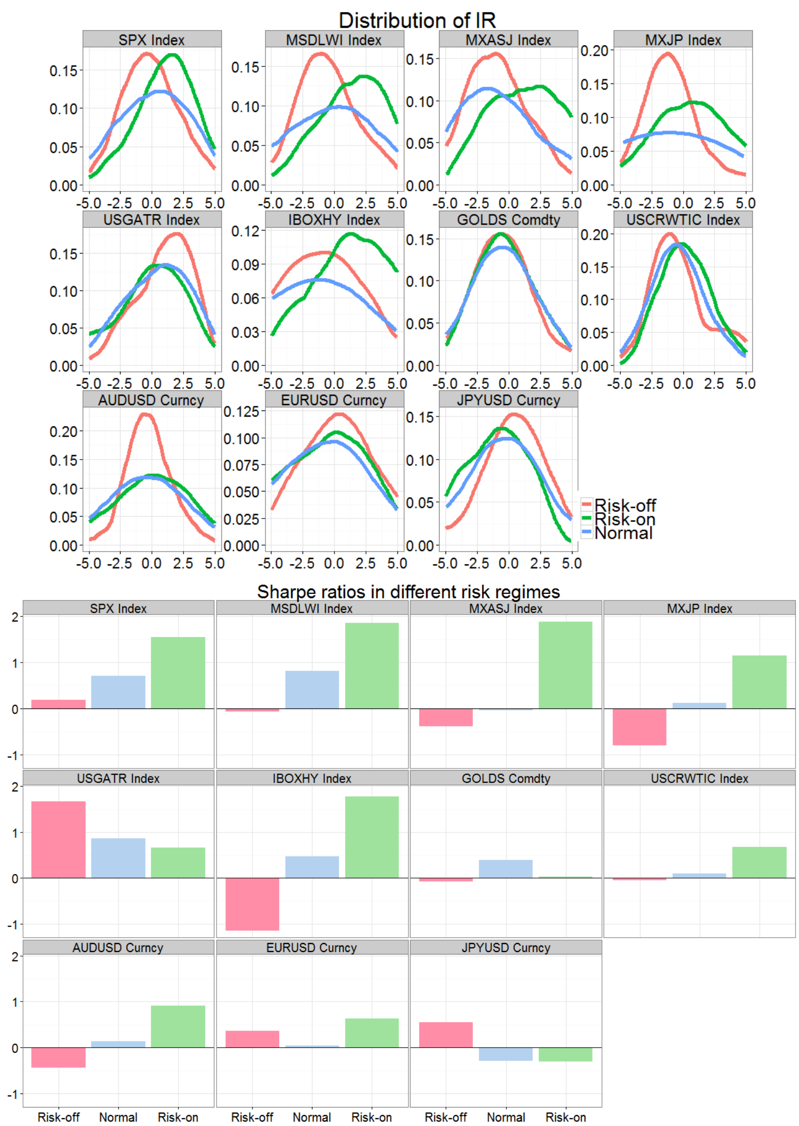
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Asset performance in different risk regimes

The figure below shows the distributions as well as the average Sharpe ratios of the assets during different risk regimes estimated using our risk aversion indicator:

- Equity returns are the most sensitive to risk regimes, and Sharpe ratios are very different in risk-on versus risk-off regimes.
- The distributions of gold returns are not clearly different between regimes.
- The assets that perform better during risk-off regimes are the US government bonds and the JPY/USD currency pair. Since government bonds and JPY are usually regarded as the "safe-haven" assets, they tend to have higher demand and appreciate during risk-off regimes.

Figure 37: Sharpe ratios of assets during different risk regimes



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Interaction between risk regimes and economic regimes

Asset returns are not only sensitive to risk regimes, but also to macro-economic regimes. A recurring question worrying investors is: are we finally in an economic growth regime? Or do we observe signs that we are moving towards an economic recession?

Economic regimes are affected by macro-variables such as inflation, GDP and interest rates. These regimes also affect investors' preferences, but probably not in the same way as risk regimes. As such, it is interesting to look at the interaction between risk and economic regimes, so that we may disentangle investors' preferences over time.

Defining global economic regimes

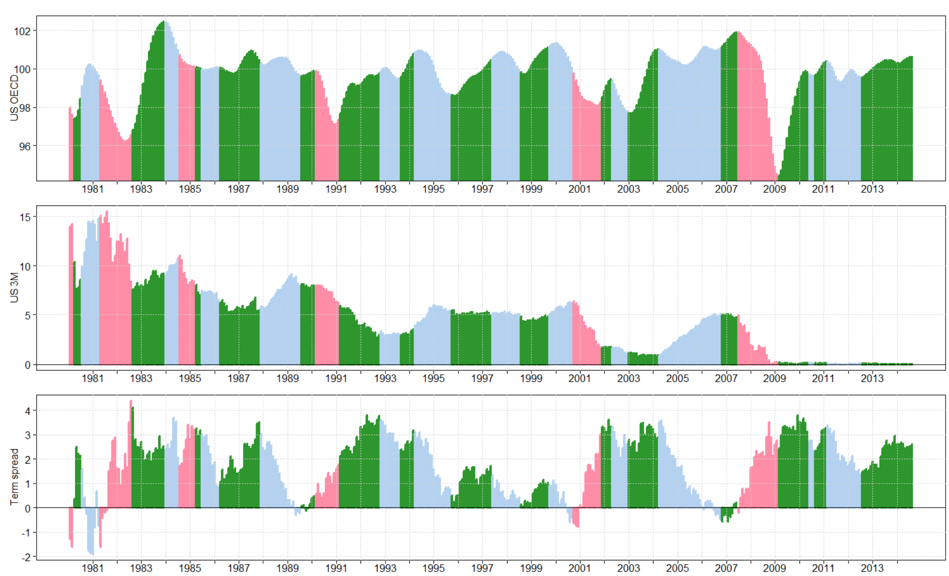
To start with, we follow the clustering approach used by our European colleagues to identify macro-regimes in the UK (Mesomeris et al., 2011)[14].

Since we are interested in global regimes, we consider US indicators as proxies. We cluster dates using 3 US-based macro-variables: US 3-month rate, US term spread (US 10-year rate over 3-month rate) and US OECD composite leading indicator, to highlight periods where they behave similarly.

We observe the following economic regimes:

- **Expansion**: Growth, increasing term spread (Green)
- **Moderate**: Moderate environment, decreasing term spread (Blue)
- **Recession**: Shrinking economy, decreasing 3-month rates (Pink)

Figure 38: Global economic regimes identified using the US OECD composite leading indicator, US 3-month rate and US term spread (10-year over 3-month). Green: Economic expansion, Blue: moderate, Pink: Recession.



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

[14] We first smooth the time series using a Hodrick-Prescott (HP) filter. Using the changes in the smoothed time series, we determine 3 clusters / regimes of dates using the *k*-means algorithm.

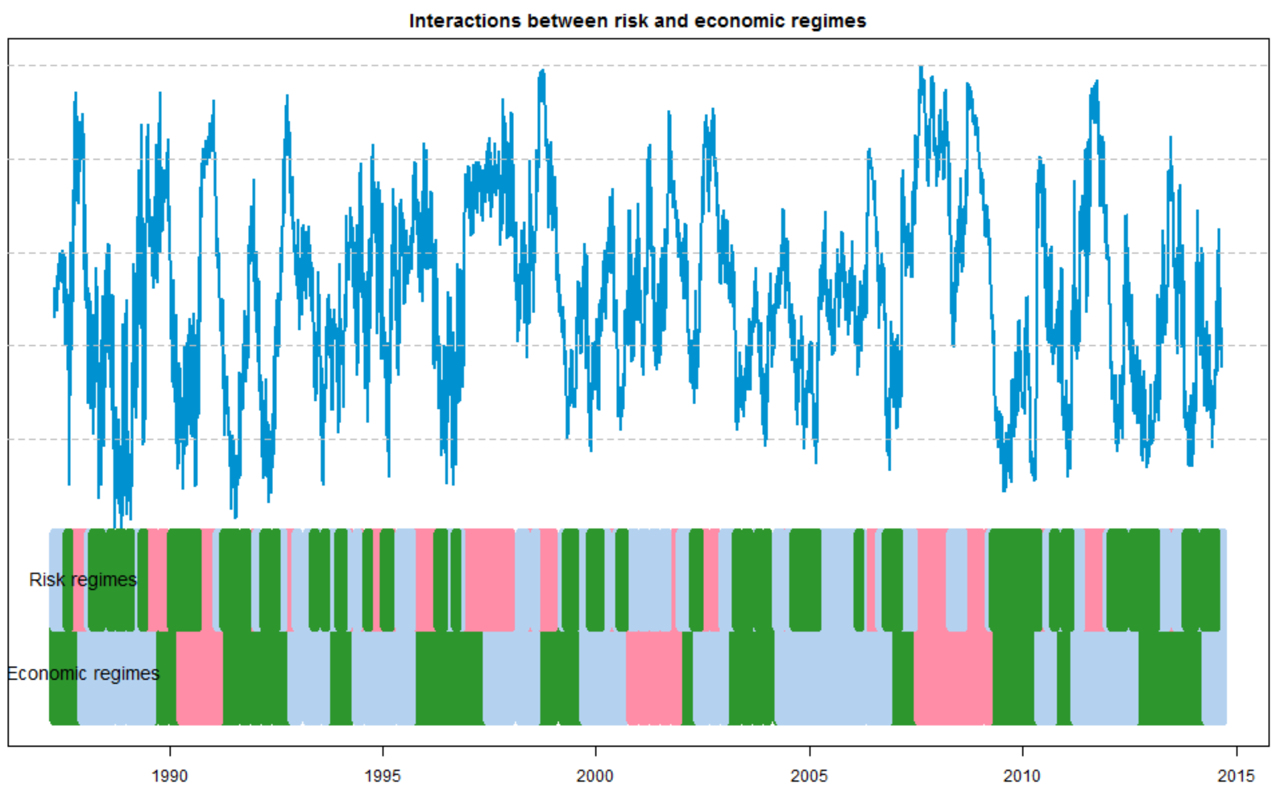
Risk regime and macro environment

Figure 39 shows the interactions between risk regimes and economic regimes. We are currently in a normal risk regime (blue) as well as a moderate economic regime (blue).

We see that risk regimes and economic regimes can behave quite differently:

- In early 1990, risk aversion was low (green) and the global economy was in a recession (pink). However this is a rare combination and we only observe this for 4 months in history.
- In 1999, we were in a risk-off regime (pink) due to the Asian Financial Crisis, but the global economy was in general expanding (green).

Figure 39: Interactions between risk and economic regimes. The blue line is our risk aversion indicator. Risk-on / Expansions are in green, Risk-off / Recessions are in pink, and blue is for Normal / Moderate regimes



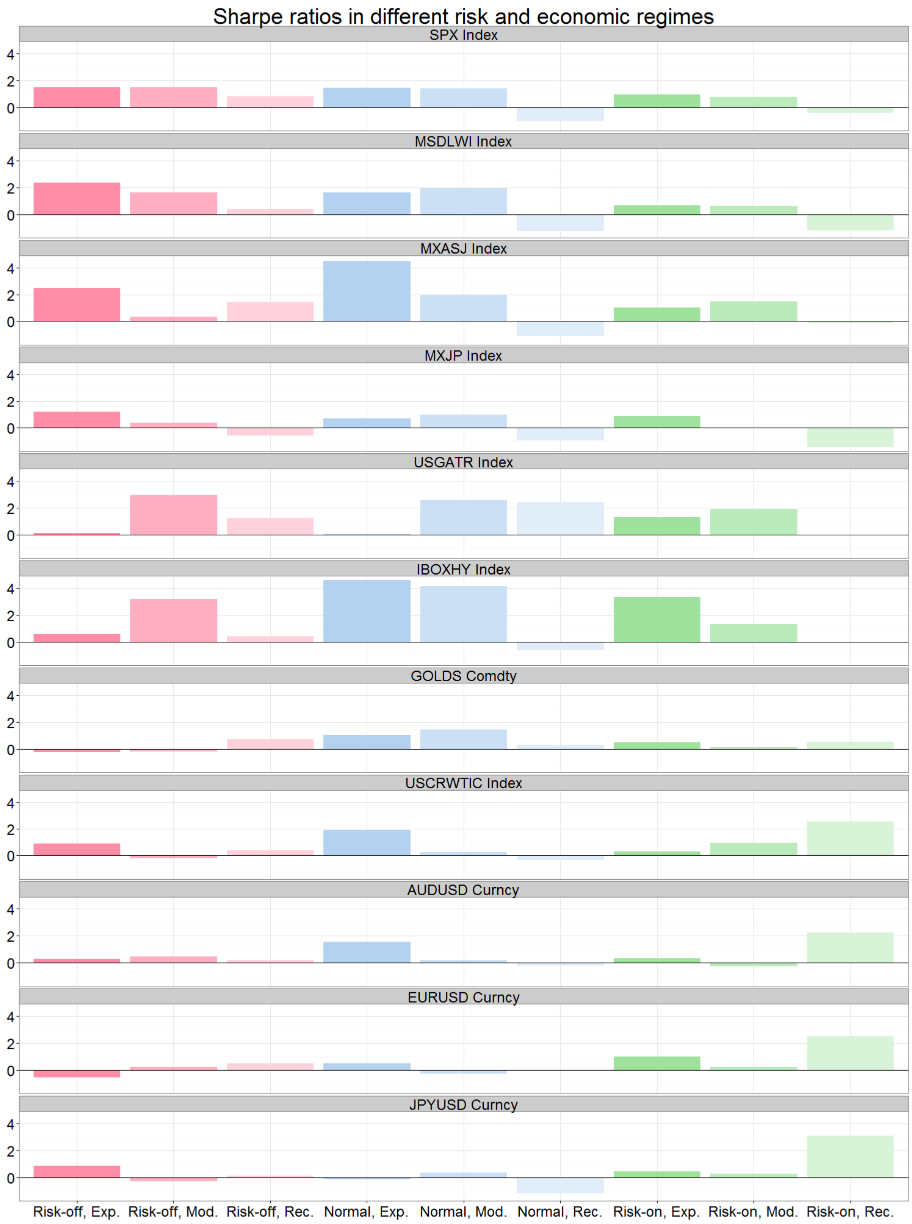
Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Asset performance in risk and economic regimes

Figure 40 shows the Sharpe ratios of different asset classes in all combinations of risk regimes and economic regimes[15].

Historically, there were 41 months with regimes similar to our current situation, i.e. normal risk and moderate economic environment. In this combination, High yield corporate bonds had the highest returns.

Figure 40: Sharpe ratios in different regimes. Darker colors correspond to economic expansion; lighter colors correspond to economic recession. Pink, blue and green are risk-off, normal and risk-on regimes respectively.



	Number of months
Risk-on, Expansion	48
Normal, Expansion	43
Normal, Moderate	41
Risk-off, Moderate	34
Risk-on, Moderate	33
Risk-off, Expansion	21
Risk-off, Recession	18
Normal, Recession	12
Risk-on, Recession	4

Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

[15] Some regime combinations only have observations for a few months; they were not removed.

Conclusions and next steps

In this note on risk, we have surveyed a large amount of literature and constructed a dynamically-weighted global risk aversion indicator, which can help investors navigate risk-on / risk-off episodes.

Main findings from this study:

- Risk aversion sectors interact with each other. In particular, risks in the Financial sector help to predict risks in the Equity market.
- Bond market risks tend to be more closely associated with risks in the Foreign exchange market.
- Using a hidden Markov model, we can identify risk regimes from our risk aversion indicator. It is more systematic than choosing an arbitrary threshold, and lets the frequency of crises change more freely. We are currently in a normal risk regime.
- Asset returns are more correlated during risk-off regimes. Also, correlations between asset classes became much higher after the Global Financial Crisis in 2008.
- Our risk aversion indicator seems to have a strong relationship with the iBoxx high yield returns, and can help predict its future performance.
- Equities are the asset class whose returns are the most sensitive to risk regimes; returns on gold do not seem to be too affected.
- In the current risk and economic situation, normal risk regime and moderate economic environment, high-yield corporate bonds have historically produced the best risk-adjusted returns.

Next steps – Tactical asset allocations

It is always challenging for investors and asset managers to time their investment decisions. As seen in this note, asset returns could behave differently across risk-on / risk-off regimes, whether it is in terms of Sharpe ratios, volatilities or correlations. Can we take advantage of the relationships between risk and returns, and come up with strategies that are immune to the ever-changing environment?

As emphasized in Ilmanen et al. (2014), tactical asset allocations based on regimes / investment environments are difficult because one has to be correct in both the forecast of regimes, and the sensitivities of asset returns to the regimes.

In the coming reports, we will focus on risk-based strategies and investigate how we can tactically allocate among asset classes across different regimes. Hopefully, we will be able to construct a portfolio which is less sensitive to the changing investment environments.

Appendix

Interpretation problems with principal component

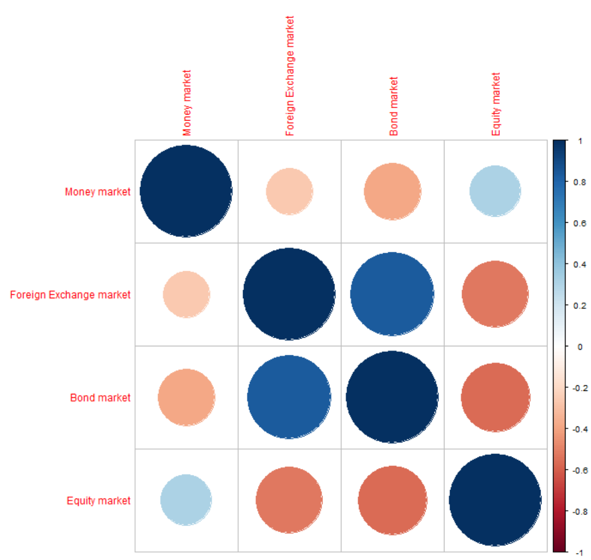
An issue with using the first principal component to construct a risk aversion indicator is the negative correlation between some of the proxies, which can translate to negative weights. Not only do they prevent us from normalizing the weights, they also mean that some of the proxies enter the model with a counter-intuitive sign.

Example:

In 1994–1995, risks in the Bond market and the Equity market were negatively correlated. At the end of 1995, the z-score of Equity market risk was negative. As it is negatively correlated with risks in the Bond market, the weight of Equity market risk is negative.

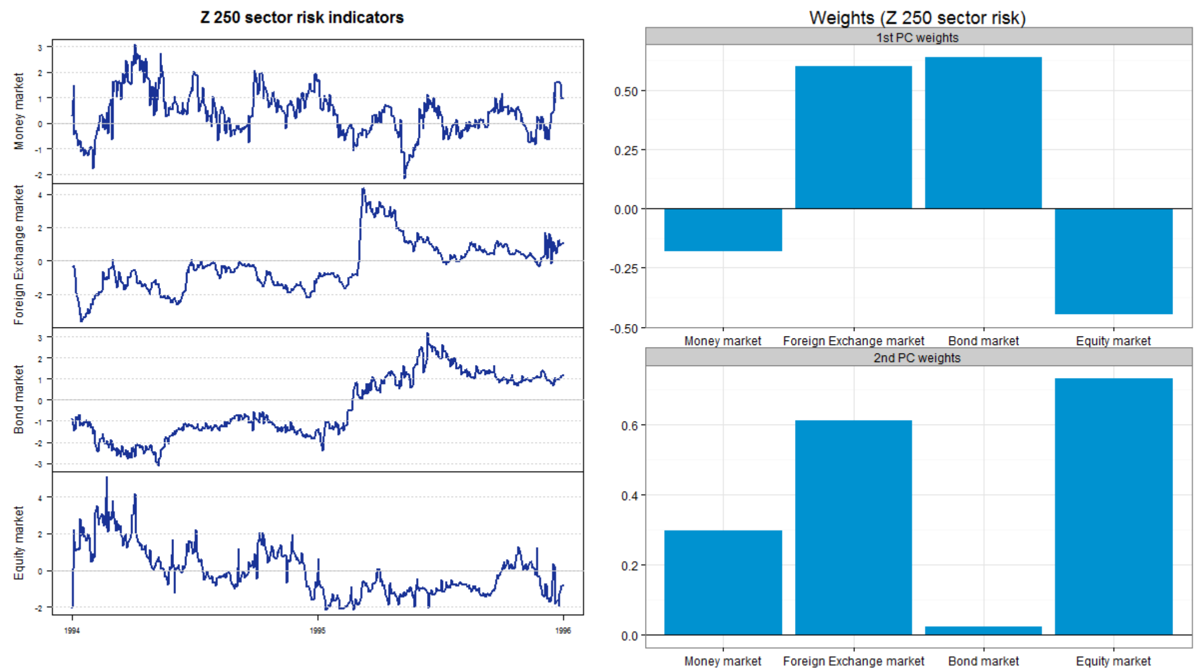
As such, despite the fact that the Equity market risk is relatively low (z-score is negative), the weighted average of risk aversion sectors becomes higher due to the large, positive contribution from the Equity market.

Figure 41: Negative correlations between Bond market and Equity market in 1994-1995

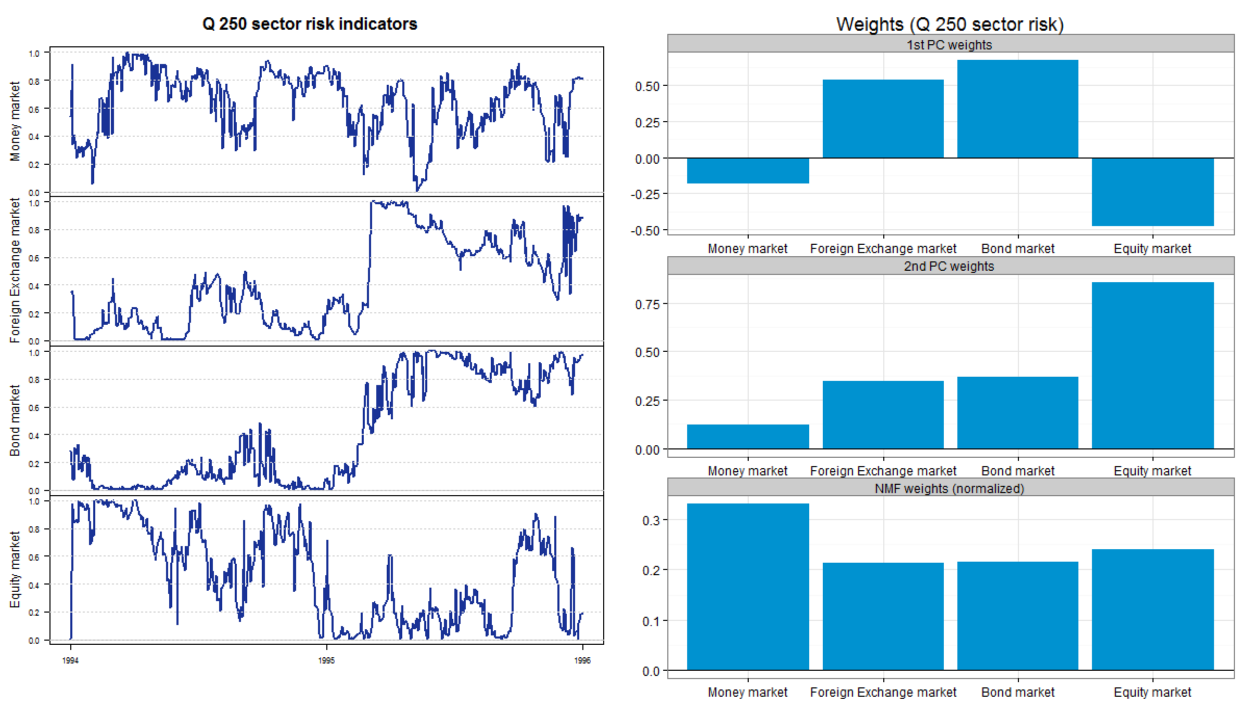


Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Figure 42: Top panels: Negative z-score for Equity market risk, and negative weight in the First Principal Component due to its negative correlations with the Bond market risk. This will lead to a positive contribution of risk from the Equity market, which is counter-intuitive.



Bottom panels: Using Quantile-scores will lead to a negative contribution of risk from the Equity market, hence 'lowering' the weighted average and agrees with what we observe in Equity market. However, we cannot normalize the weights



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Non-negative matrix factorization (NMF)

In non-negative matrix factorization, given an $n \times p$ matrix X with non-negative coefficients (e.g., the p column vectors could be our risk aversion sectors), we look for matrices F and W with non-negative coefficients, such that

$$X \approx F \times W .$$

The columns of the $n \times r$ matrix F are the factors, and W is an $r \times p$ matrix of weights for each factor.

Most NMF algorithms update F and W iteratively, and minimize some loss function. In this report, we minimize the Kullback-Leibler divergence between X and $F \times W$.

Gaujoux (2010) provides details on the implementation of non-negative matrix factorization in *R*.

Timeline of historical crisis

The following historical crisis episodes are used to evaluate performance of risk aversion indicators. Some crises may actually last for a few years, but we try to highlight the months which were the most stressful. Crises which are close to each other are merged together.

Figure 43: Timeline of historical crisis since 1987

	Date	Start	End	Event
Black Monday	1987-10-19	1987-10-01	1988-02-01	Dow Jones plunged by 508 points
Japanese bubble	1989-12-29	1989-12-29	1990-06-30	The monetary tightening policy in 1989 lead to sharp fall in stock prices in early 1990
Scandinavian crisis	1991-12-02	1991-09-19	1992-01-31	SKOP's liquidity position finally collapsed, the Bank of Finland took over the control of SKOP, Credit crunch
ERM crisis, Black Wednesday	1992-09-01	1992-07-18	1993-08-30	Many currencies devalued and drop link with ERM, British government was forced to withdraw the pound from the European ERM. EC governments raise interest rates in effort to protect ERM
Bond market crisis	1994-10-03	1994-04-01	1994-11-30	Bond market suffered a very sharp and sudden selloff that started in the U.S. and Japan and then spread more or less across all developed markets. The yield on the 30-year U.S. Treasury long bond jumped more than 100 bps
Mexican crisis	1994-12-15	1994-12-15	1995-06-30	The new government announced the Mexican central bank's devaluation of the peso between 13% and 15% foreign investors fleeing emerging market investments
Asian crisis, LTCM crisis, Dow Jones crash	1997-07-02	1997-07-02	1998-03-31	Financial collapse of the Thai baht, most of Southeast Asia and Japan saw slumping currencies, devalued stock markets and other asset prices. Korea currency crisis. LTCM crashed on 1997-09-22. Dow Jones down 7.2 % on 1997-10-27
Russian financial crisis	1998-08-17	1998-05-18	1998-09-30	The Russian government and the Russian Central Bank devalued the Ruble and defaulted its debt
Brazil financial crisis	1999-01-15	1999-01-15	1999-05-30	35% drop in the value of the Brazilian real
Dot-com bubble	2000-03-10	2000-02-01	2000-09-30	Dot-com bubble burst, NASDAQ fell
Global recession, Turkish crisis	2001-02-20	2001-01-01	2001-06-30	Economic recession in developed markets. Turkish stocks plummeted and the interest rate spiked, Turkish central bank to lose USD 5 billion of its reserves
9-11 attack	2001-09-11	2001-09-11	2001-10-30	9-11 terrorist attack
Argentina debt default, Enron bankruptcy	2001-10-16	2001-12-01	2002-01-31	Argentina debt default in December 2001, abandoned the peso–dollar parity in Jan 2002
Stock market crash	2002-10-09	2002-08-30	2003-03-30	Sharp drop of Dow Jones and NASDAQ
Hurricane Katrina	2005-08-25	2005-08-25	2005-09-30	Hurricane Katrina
China bubble	2007-02-27	2007-01-01	2007-05-30	China's economy overheat, the SSE Composite Index of the Shanghai Stock Exchange tumbled 9%, the largest drop in 10 years
Subprime crisis	2007-10-11	2007-08-01	2007-11-30	Massive write downs on the value of loans, MBS and CDOs
Bear Stearns collapse	2008-03-13	2008-01-01	2008-06-30	Bear Stearns collapse due to subprime crisis
Lehman collapse	2008-09-16	2008-08-01	2008-11-30	Bankruptcy of Lehman Brothers
Dubai debt crisis	2009-11-26	2009-11-01	2010-01-24	Dubai World proposed to delay repayment of its debt. Shares dropped in Dubai and Abu Dhabi by 7.3% and 8.3%
Greece crisis, flash crash	2010-04-27	2010-03-01	2010-08-30	Standard and Poor's downgrades Greece's debt ratings below investment grade to junk bond status. Flash crash on 2010-05-06
Japanese earthquake	2011-03-11	2011-03-11	2011-04-30	Japanese earthquake
Stock market downturn	2011-08-08	2011-08-01	2011-10-01	Sharp drop in stock prices globally due to fears of EU sovereign debt crisis, concerns over US and France's rating
Spain debt crisis	2012-05-09	2012-03-01	2012-07-26	Spain's largest mortgage lender, Bankia bank, was nationalized on 9 May. In June, the Spanish 10-year government bond reached 7% and Spanish CDS is at record high of 633 bps
US debt ceiling	2013-05-19	2013-05-19	2013-10-17	The United States hits the debt ceiling on 2013-05-19, fear of default

Source: Deutsche Bank Quantitative Strategy

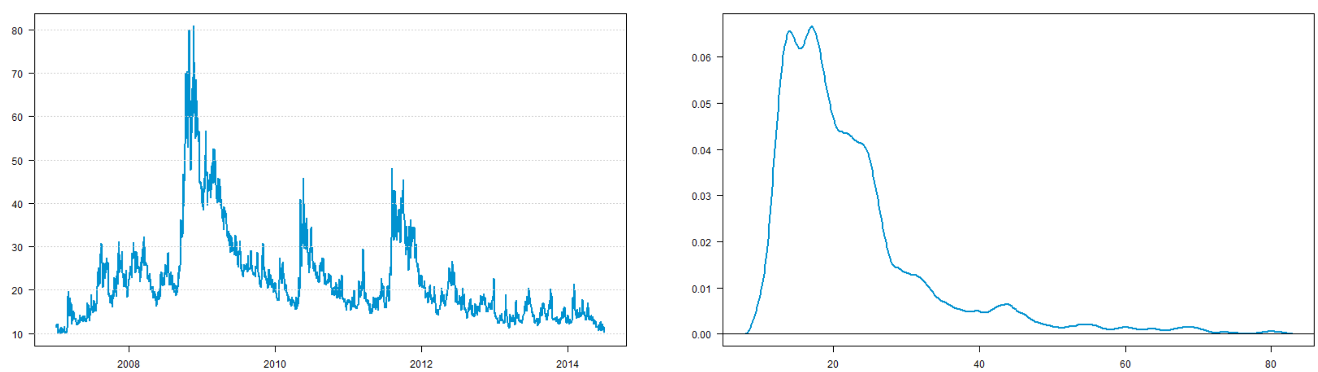
Identifying regimes using Hidden Markov Models (HMM)

Model set up and structure

In a hidden Markov model, the system (e.g., the economy, or some asset we are interested in), can be in different states (e.g., "volatile" and "calm"), that change over time. The evolution of the states is described by a Markov chain, i.e., the probability of being in a given state at time t+1 depends on the state at time t, but not on previous states. The state is not observed: what we observe is a draw from a distribution associated with (conditional on) the current state (for instance, the return distribution for the "volatile" state could have a negative mean and high variance, while the distribution for the "calm" state could have a positive mean and a smaller variance).

Below is an example from VIX which seems to have 2-3 mixed distributions with different means and variances.

Figure 44: Time variations and distribution of VIX – 2 or 3 regimes could exist, resulting in some mixed distributions



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

The Hidden Markov Model consists of 3 parts:

- **Prior model**: Prior distribution of the states (E.g. assume a multinomial distributions)
- **Transition model**: Transition probabilities between the states
- **Response model**: Conditional distributions of the observations given the states (e.g. Gaussian distributions)

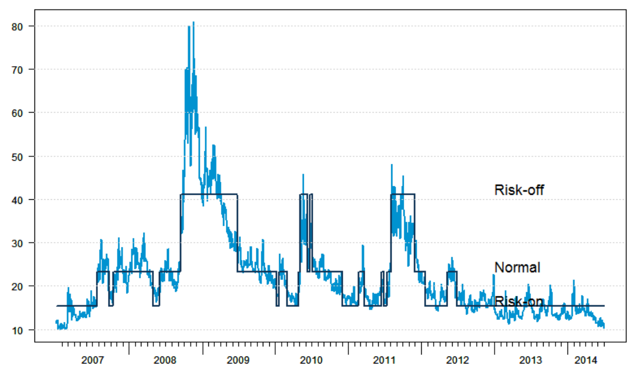
Parameters are estimated by maximizing the joint likelihood of the observations and the states. As the states are latent, one can use the Expectation-Maximization (EM) algorithm.

Example: VIX

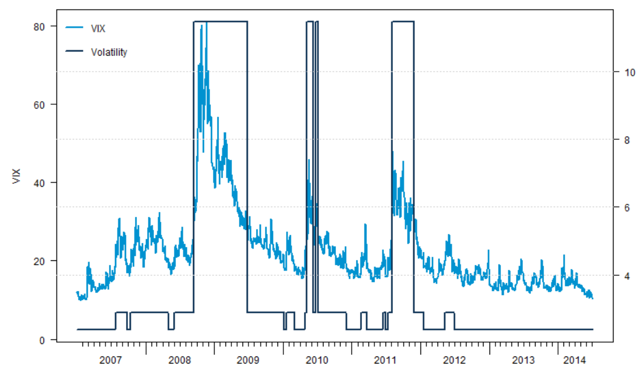
We fit a simple HMM on the VIX with 3 states, and assume that the observations are Gaussian conditional on the states. Having estimated the mean and variance of the distributions in each state, we associate the risk-off regimes (pink) with the highest mean, and the risk-on regimes (green) with the lowest mean.

Figure 45: Example of fitting a Hidden Markov Model on VIX

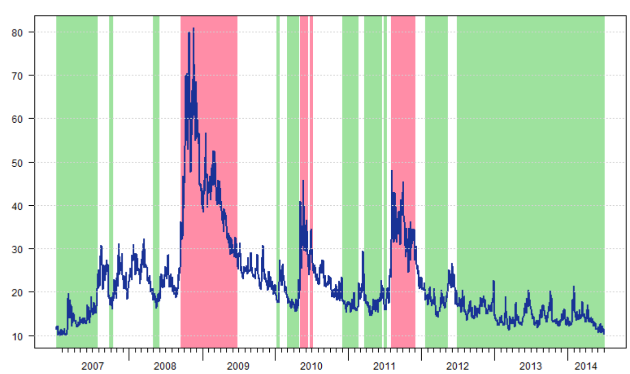
Conditional means changes with regimes



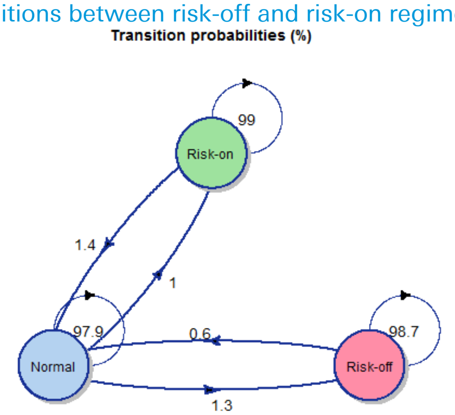
Conditional variances changes with regimes



Risk-off regimes (pink) are associated with the highest mean, and risk-on regimes (green) with the lowest mean



Transition probabilities: A constraint is imposed to forbid transitions between risk-off and risk-on regimes



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

Bayesian network

Visualizing conditional dependencies

A Bayesian network is a way of decomposing a joint probability distribution into a product of simpler (lower-dimensional) distributions. Consider for instance three variables *A*, *B* and *C*.

- If *A, B* and *C* are independent, Their joint probability distribution can be factored as $P(A,B,C) = P(A)P(B)P(C)$. The corresponding Bayesian network has three unconnected nodes.
- If *A and* (*B*,*C*) are independent, we have two natural decompositions:

$$\begin{aligned} P(A,B,C) &= P(A)P(B,C) = P(A)P(B)P(C \mid B) \\ &= P(A)P(C)P(B \mid C) \end{aligned}$$

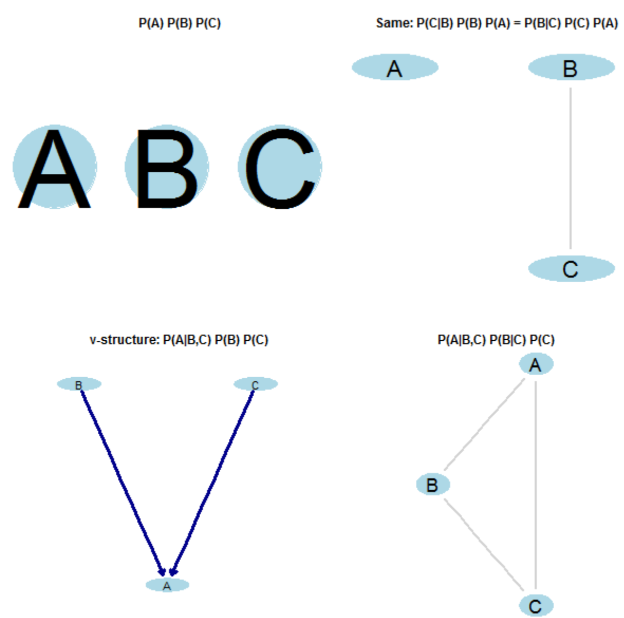
  They correspond to two different networks, with a single edge, either $B \to C$ or $C \to B$.

- If there are no independence relations, we have six possible decompositions, with one of them being

$$P(A,B,C) = P(A)P(B \mid A)P(C \mid A,B)$$

  and the other decompositions are permutations of *A*, *B*, *C* in the above. They correspond to the complete graph on three vertices, with all the possible edge orientations. But what Bayesian networks attempt to encode is actually not dependencies, or independencies, but conditional independencies. For instance, if *B* and *C* are conditionally independent given *A*, i.e. $B \perp C \mid A$, the joint distribution can be factored as $P(A,B,C) = P(B)P(C)P(A \mid B,C)$. In this case, the direction of the edges is well-determined.

Figure 46: Bayesian networks are probabilistic graphical models



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

More generally, a Directed Acyclic Graph whose vertices correspond to random variables defines a factorization of their joint distribution as

$$P = \prod_{V \in Vertices} P[V \mid parents(V)]$$

When we fit a Bayesian network to data, we are looking for a graph whose associated factorization is consistent with the data, and we want it to be as "small" as possible, i.e. to have as many low-dimensional factors as possible. As seen in the example above, it may not be unique.

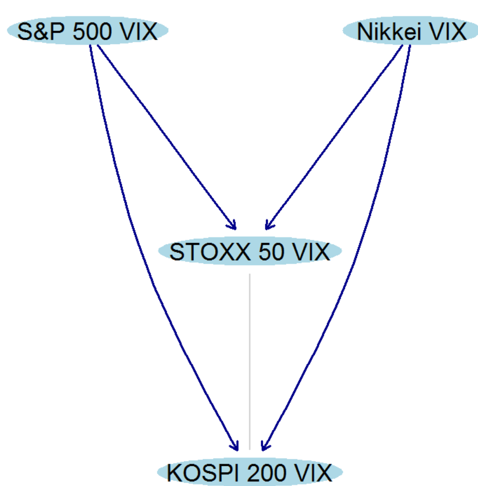
To reduce the effect of noise in the estimation, we estimate many Bayesian networks on different bootstrap samples, and only keep the edges that appear often enough.

Example: VIX

As an example, Figure 47 looks at 4 equity implied volatilities on the S&P 500, STOXX 50, Nikkei and KOSPI 200 (the Nikkei VIX and KOSPI 200 VIX were lagged by 1 day). We see that

- The distributions of STOXX 50 VIX and KOSPI 200 VIX are dependent on S&P 500 VIX and Nikkei VIX.
- The STOXX 50 VIX and KOSPI 200 VIX are dependent, but we do not have enough information to suggest a direction.

Figure 47: Example of Bayesian network of VIX



Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

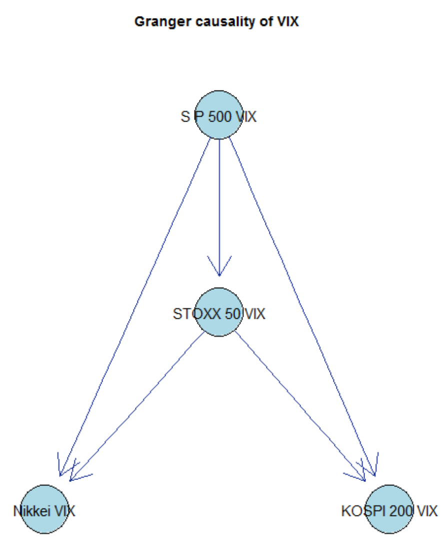
Granger causality test

The Granger causality test (Granger 1969) attempts to find evidence if the past values of a variable *X* help forecast another variable *Y*, and takes into account the past values of *Y* through a VAR model. For each pair of variables, we select the optimal number of lags in the bivariate VAR model using the AIC. The maximum lag is set to 10 days.

The test basically considers the relevant coefficients on the lagged variables of *X* and applies an *F* test to see if these coefficients are jointly zero. In other words, the null hypothesis is that *X* does not Granger-cause *Y*. We use the bootstrap (1000 replications) to reduce sampling variance. Based on the *p*-values of the test, we construct a directed graph to display the lead / lag relationships between the variables.

In the following example, we consider again the 4 equity implied vols. It shows that past information in S&P 500 VIX helps to predict the VIX in the European as well as the Asian markets.

Figure 48: Example: lead-lag relationships of VIX



p-values of Granger causality test (E.g. $p < 0.01$ rejects the null hypothesis).
VIX on the rows are the causes, and those on the columns are the effects.

	S P 500 VIX	Nikkei VIX	STOXX 50 VIX	KOSPI 200 VIX
S P 500 VIX		0.000	0.000	0.000
Nikkei VIX	0.553		0.884	0.774
STOXX 50 VIX	0.110	0.000		0.000
KOSPI 200 VIX	0.415	0.329	0.552	

Source: S&P, Thomson Reuters, Bloomberg Finance LP, Deutsche Bank Quantitative Strategy

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Appendix 1

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