Journal of Banking & Finance 67 (2016) 103–118

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

What do asset prices have to say about risk appetite and uncertainty? ☆,☆☆

Geert Bekaert [a], Marie Hoerova [b,*]

[a] Columbia University, United States
[b] European Central Bank, Germany

ARTICLE INFO

Article history:
Received 30 September 2012
Accepted 26 June 2015
Available online 4 July 2015

JEL classification:
G12
E44

Keywords:
Economic uncertainty
Risk aversion
Time variation in risk and return
Credit spread
Volatility dynamics
Financial stress

ABSTRACT

Building on intuition from the dynamic asset pricing literature, we uncover unobserved risk aversion and fundamental uncertainty from the observed time series of the variance premium and the credit spread while controlling for the conditional variance of stock returns, expectations about the macroeconomic outlook, and interest rates. We apply this methodology to monthly data from both Germany and the US. We find that the variance premium contains a substantial amount of information about risk aversion whereas the credit spread has a lot to say about uncertainty. We link our risk aversion and uncertainty estimates to practitioner and "academic" risk aversion indices, sentiment indices, financial stress indices, business cycle indicators and liquidity measures.

1. Introduction

Since the Great Recession, there has been a proliferation of research on stress indices, flight to quality indicators and uncertainty measures, whereas existing practitioner and academic measures of risk aversion and "sentiment" (see e.g. Baker and Wurgler, 2006) have received renewed attention as monitoring tools in the volatile economic environment. Some recent studies point to a potential link between loose monetary policy and the risk appetite of market participants, spurring a literature on what structural economic factors would drive risk aversion changes (see, e.g., Rajan, 2006; Bekaert et al., 2013).

Our goal in this paper is to link all of these measures to two fundamental concepts, risk aversion and economic uncertainty, which recent structural dynamic asset pricing models, such as Campbell and Cochrane (1999) and Bansal and Yaron (2004), have identified as important drivers of asset price dynamics. In particular, Campbell and Cochrane (1999) show that a model with countercyclical risk aversion accounts for a large equity premium, and substantial variation in returns and price-dividend ratios. According to their model, investors fear stocks primarily because they do poorly in recessions, when their consumption levels fall close to a "habit stock". Menzly et al. (2004), Brandt and Wang (2003) and Wachter (2006) present related consumption-based models of time-varying risk aversion, whereas Bekaert et al. (2010) show that changes in risk aversion that are not fully driven by fundamentals are essential in fully capturing asset price dynamics. Reduced-form asset pricing models, focused on simultaneously explaining stock return dynamics and option prices, have also concluded that time-varying prices of risk are important drivers of stock return and option price dynamics (see Bollerslev et al., 2011; Gai and Vause, 2006). Bansal and Yaron (2004) and Bansal et al. (2005), among others, focus on economic uncertainty as a source of fluctuations in asset prices and risk premiums.

In this article, we develop measures of time-varying risk aversion and uncertainty that are relatively easy to estimate or compute, so that they can be compared to the many indices referred

☆ This paper was submitted long before Geert Bekaert became Co-Managing Editor at the Journal; Turan Bali served as the Managing Editor for this manuscript.

☆☆ We are grateful to Sandra Schmidt for providing the ZEW Financial Market survey data and to Marco Lo Duca and Jana Urbankova for excellent research assistance. This is a much expanded version of Bekaert et al. (2009b), and we thank Martin Scheicher for earlier inputs. The views expressed in this paper do not necessarily reflect those of the European Central Bank or the Eurosystem.

* Corresponding author at: Financial Research Division, European Central Bank, Sonnemannstrasse 20, D-60314 Frankfurt am Main, Germany.

http://dx.doi.org/10.1016/j.jbankfin.2015.06.015
0378-4266/

to above. The model we use is inspired by the dynamic asset pricing literature. In particular, we view risk aversion and economic uncertainty as two main drivers of asset pricing dynamics and model them as latent variables as in Bekaert et al. (2009a). However, we do not impose the strong restrictions structural models would impose on the dynamics of asset prices. Instead, we achieve identification by using multiple asset prices (as is often the case in the practitioners' literature) and economically inspired restrictions on the dynamics of these variables. In particular, we lean heavily on the idea that the implied volatility indices (like the VIX) should have information about risk parameters, once they are cleansed of the influence of normal volatility dynamics and uncertainty (see also Bekaert et al., 2013; Duan and Yeh, 2010).

The dynamic asset pricing and options literatures indirectly reveal the difficulty in interpreting many existing risk aversion indicators. Often they use information such as the VIX or return risk premiums that are obviously driven by both the amount of risk and risk aversion. Disentangling the two is not straightforward. Articles such as Bollerslev et al. (2011) and Drechsler and Yaron (2011) point towards the use of the VIX in combination with the (conditional) expected variance as particularly informative about risk preferences. While both should be closely associated with economic uncertainty, the conditional variance of equity returns is likely to be much less affected by risk preferences than the VIX. We therefore use the difference between the (squared) VIX and the conditional variance – the so-called equity variance premium – as a proxy for risk aversion. We also use other financial variables, namely the credit spread, the term spread, conditional equity variance and a short-term interest rate, to extract additional information about economic uncertainty and risk aversion.

The identification strategy we employ is akin to the identification strategy in old work by Hamilton (1985) and Fama and Schwert (1979), trying to identify the real rate process from data on nominal interest rates and inflation through parametric assumptions on the dynamics of the various variables. The methodology is simple and easily generalizable to include additional asset prices and other potential determinants of risk aversion and uncertainty.

We apply the technique to uncover risk aversion and uncertainty for Germany and the US. Our sample period is January 1992 to March 2008. We find both series to be highly persistent in both countries. Moreover, the two risk aversion series show a significant comovement across countries and US risk aversion Granger causes German risk aversion. We also analyze links between the uncovered variables and various observable series. The variance premium contains a substantial amount of information regarding risk aversion in both countries. The credit spread primarily contains information about economic uncertainty.

The rest of the paper is organized as follows. Section 2 presents the model and estimation strategy in detail. Section 3 outlines the data we use. Section 4 presents risk aversion and uncertainty estimates extracted from asset prices. Section 5 links the risk aversion and uncertainty measures to practitioner and "academic" risk aversion indices, sentiment indices, financial stress indices, business cycle indicators and liquidity measures. The final section concludes and previews future work.

2. The model

We develop a parsimonious empirical strategy to uncover unobserved risk aversion and fundamental uncertainty from observed time series of the variance premium, conditional variance, and other asset prices. Our approach is to follow the dynamic asset pricing literature in spirit. That is, we specify the state variable dynamics with risk aversion and uncertainty as two key latent variables. However, we do not model the pricing kernel. There is much disagreement about how preferences must be modelled and hence, the specification of the kernel would very much color what risk aversion process is implied. Instead, we simply assume that there is a linear mapping between the variance premium, the conditional variance, and other asset prices on the one hand and the state variables on the other hand. While this relationship cannot literally be linear in any asset pricing model, it may prove a good first-order approximation. For example, Bekaert et al. (2009a) show that in their model the equity premium and price-dividend ratio are well approximated by a linear function of the two key state variables, uncertainty, and risk aversion. The cost of the approach is that we cannot rely on a model to attain identification. Hence, our identification comes from restrictions on the dynamics of the state variables and the mapping between state variables and endogenous variables.

Let's start with a simple model with four state variables, which we collect in the vector X_t:

$$X_t = [uc_t, ra_t, i_t, muc_t]',$$

where uc_t denotes fundamental uncertainty, ra_t denotes risk aversion, i_t is the short-term interest rate, and muc_t stands for survey uncertainty about the macroeconomic outlook. While i_t and muc_t are observable, uc_t and ra_t are latent variables.

In a structural model, the interest rate process would be endogenous. While we take it to be exogenous in our framework, we model its dynamics to be consistent with standard structural asset pricing models. We add uncertainty about the macroeconomic outlook as an observable proxy to true uncertainty. The model could be easily generalized to allow for a large number of proxies for macroeconomic uncertainty, and we could also introduce observable proxies for risk aversion.

Our major identifying assumption is to model uncertainty and risk aversion as simple univariate but heteroskedastic autoregressive processes:

$$\begin{aligned} uc_t &= \mu_{uc} + \phi_{uc} uc_{t-1} + \sigma_{uc}\sqrt{muc_{t-1}}e_t^{uc} \\ ra_t &= \mu_{ra} + \phi_{ra} ra_{t-1} + \sigma_{ra}\sqrt{muc_{t-1}}e_t^{ra}. \end{aligned} \tag{1}$$

Hence, we assume that the variability of uncertainty and risk aversion increases when macroeconomic uncertainty is higher.

The interest rate process is inspired by a standard consumption-based asset pricing model, such as Bekaert et al. (2009a):

$$i_t = \gamma_1 ra_t + \gamma_2 muc_t + \phi_i i_{t-1} + \sigma_i\sqrt{i_{t-1}}e_t^i. \tag{2}$$

We would expect γ_2 to be negative, reflecting precautionary savings demand. However, the link between risk aversion and the interest rate cannot be signed, as it may reflect both utility smoothing and precautionary savings motives. We also introduce heteroskedasticity of the square-root form.

We treat survey uncertainty muc_t as a proxy for the unobserved fundamental uncertainty:

$$muc_t = uc_t + \phi_{muc} muc_{t-1} + \sigma_{muc}\sqrt{muc_{t-1}}e_t^{muc},$$

i.e. muc_t provides a noisy signal about true uncertainty. Most empirical measures of economic uncertainty are clearly imperfect proxies to true economic uncertainty. We also allow for additional autoregressive effects, because our measure of uncertainty forecasts over a somewhat longer horizon than our data frequency, so this term helps clean up autocorrelation in the observed muc_t series. Finally, we model muc_t as heteroskedastic with its variance increasing in its level.

If we bring these processes together, X_t follows a simple first-order autoregressive process:

$$X_t = \mu_x + \Phi_x X_{t-1} + \varepsilon_t^x,$$

where $\mu_x = [\mu_{uc}, \mu_{ra}, \mu_i, \mu_{uc}]'$ is the vector of drifts of the state variables, ε_t^x is the vector of innovations, and

$$\Phi_x = \begin{bmatrix} \phi_{uc} & 0 & 0 & 0 \\ 0 & \phi_{ra} & 0 & 0 \\ 0 & \gamma_1\phi_{ra} & \phi_i & \gamma_2\phi_{muc} \\ \phi_{uc} & 0 & 0 & \phi_{muc} \end{bmatrix}. \tag{3}$$

Let $\varepsilon_t^x = \Sigma_{x,t-1} e_t^x$ with $e_t^x \sim N(0, I)$. It follows that

$$\Sigma_{x,t-1} = \begin{bmatrix} \sigma_{uc}\sqrt{muc_{t-1}} & 0 & 0 & 0 \\ 0 & \sigma_{ra}\sqrt{muc_{t-1}} & 0 & 0 \\ 0 & \gamma_1\sigma_{ra}\sqrt{muc_{t-1}} & \sigma_i\sqrt{i_{t-1}} & \gamma_2\sigma_{muc}\sqrt{muc_{t-1}} \\ \sigma_{uc}\sqrt{muc_{t-1}} & 0 & 0 & \sigma_{muc}\sqrt{muc_{t-1}} \end{bmatrix} \tag{4}$$

so that $\Sigma_{x,t-1}$ contains the standard deviations of the state variables' shocks.

To identify the dynamics of the state variables, we conjecture that a number of observable asset prices or asset price characteristics are an affine function of the state variables:

$$Y_t = b_y + B_y X_t + u_t.$$

For identification purposes we set $b_y = 0$. Two elements of Y_t are simply the "observed" state variables, in our case i_t and muc_t. The dimension of Y_t can be arbitrarily large but it must be at least as large as the dimension of X_t. When $\dim(Y_t) > \dim(X_t)$, stochastic singularities arise, which is why we introduce measurement error, u_t. Our identification strategy is to split up $Y_t = \left[Y_t^{1\prime}, Y_t^{2\prime}\right]'$, where Y_t^1 has the same dimension as X_t and is used to "invert" the state variables. The remaining elements in Y_t, Y_t^2, are then assumed to be measured with error relative to the model; consequently, $u_t = \left[0, u_t^{2\prime}\right]'$. For future reference, let us also decompose

$$B_y = \begin{bmatrix} B_y^1 \\ B_y^2 \end{bmatrix}.$$

With this notation in hand, it is straightforward to write down the likelihood function for Y_t. Using $X_t = \left[B_y^1\right]^{-1} Y_t^1$, the dynamics for Y_t can be described as follows:

$$Y_t^1 = \mu_y^1 + A_y^1 Y_{t-1}^1 + B_y^1 \varepsilon_t^x \tag{5}$$

$$Y_t^2 = B_y^2 \left[B_y^1\right]^{-1} Y_t^1 + u_t^2, \tag{6}$$

where $\mu_y^1 = B_y^1 \mu_x$ and $A_y^1 = B_y^1 \Phi_x \left[B_y^1\right]^{-1}$. Define $\varepsilon_t^y = \left[\left(B_y^1 \varepsilon_t^x\right)', u_t^{2\prime}\right]'$, then,

$$\Sigma_{y,t-1} = \begin{bmatrix} B_y^1 \Sigma_{x,t-1} & 0 \\ 0 & \Sigma_u \end{bmatrix}$$

where Σ_u is a diagonal matrix of measurement error standard deviations. The likelihood function can then be written as

$$\mathcal{L} = -\frac{Tn}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log\left[\det\left(\Sigma_{y,t-1}^2\right)\right] - \frac{1}{2}\sum_{t=1}^{T}\left(\varepsilon_t^{y\prime}\Sigma_{y,t-1}^{-2}\varepsilon_t^y\right). \tag{7}$$

As a practical application, we let

$$Y_t^1 = [cs_t, vp_t, i_t, muc_t]'$$

and

$$Y_t^2 = [ts_t, cv_t]'$$

where cs_t is the credit spread, which is generally believed to be very sensitive to investor risk appetites and vp_t is the equity variance premium. Other variables that may have additional information on risk aversion and uncertainty are the term spread, ts_t, and the conditional equity variance, cv_t. These variables should react to both risk aversion and uncertainty and the interest rate.[1]

Our crucial identifying assumption is that vp_t varies only due to the two unobserved factors, uc_t and ra_t. In particular, we impose that:

$$B_y^1 = \begin{bmatrix} B_{cs}^{uc} & B_{cs}^{ra} & B_{cs}^{i} & 0 \\ B_{vp}^{uc} & B_{vp}^{ra} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

and

$$B_y^2 = \begin{bmatrix} B_{ts}^{uc} & B_{ts}^{ra} & B_{ts}^{i} & 0 \\ B_{cv}^{uc} & B_{cv}^{ra} & B_{cv}^{i} & 0 \end{bmatrix}.$$

To obtain identification, we also assume that $B_{vp}^{ra} = 1$. This is tantamount to using cs and vp to determine the level of uc_t and ra_t. Moreover, we assume that, once movements of uncertainty are controlled for, the variance premium and risk aversion move one-to-one.

If we substitute the Y_t^1 dynamics in the Y_t^2 equation in (6), we have a VAR on Y_t with a number of cross-equation restrictions. A necessary condition for identification is that the number of parameters in the unconstrained VAR for Y_t exceeds the number of parameters in the model we specify. It is easily verified that this is the case in the current specification. A natural test of the model is to compare the likelihood of an unconstrained VAR relative to the likelihood of our model.

While only cs_t, vp_t, and i_t are used directly in uncovering the unobservables, the information content in ts_t and cv_t enters the estimation of the parameters in B_y. Naturally, alternative specifications are possible in which, for example, cv_t is used to estimate the unobservables directly, while cs_t enters the estimation indirectly. We have estimated such alternative models, finding the implied risk aversion measures to be highly correlated across different specifications.

3. Data

Our sample, extending from January 1992 to March 2008, comprises US and German realized and implied stock market volatilities (used to estimate conditional variances of stock returns and equity variance premia), interest rates, credit spreads, and survey-based expectations about the macroeconomic outlook. Table 1 lists the model input variables, their definitions, and data sources.

To obtain estimates of conditional variances of stock returns, and of equity variance premia, we use a decomposition of the squared implied volatility indices, the VIX index for the US and the VDAX index for Germany. The VIX is based on a weighted average of S&P 500 options that straddle a 30-day maturity, i.e. a fixed horizon of 22 trading days (see CBOE (2004) for more details). These options are European-style out-of-the money puts and calls of 2 nearest to 30 calendar days expiries, covering a wide range of strikes. The shorter-horizon options are restricted to a maturity in excess of eight days. The number of strike prices included is depen-

[1] At this point, we do not use stock market information because it is quite difficult to control for cash flow expectations in the context of the current model without considerably increasing the state space. Moreover, we simply do not have adequate data for Germany to do so.

Table 1
Description of model input variables.

Variable	Description	Source
USA		
Conditional variance	VIX decomposition	See Section 3
Credit spread	BAA – AAA yield spread	FRED
Long rate	10-Year government bond rate	Datastream
Macro uncertainty	Survey dispersion	ZEW
Short rate	3-Month Treasury bill rate	Datastream
Variance premium	VIX decomposition	See Section 3
Germany		
Conditional variance	VDAX decomposition	See Section 3
Credit spread	Corporate – public yield spread	Bundesbank
Long rate	10-Year government bond rate	Datastream
Macro uncertainty	Survey dispersion	ZEW
Short rate	3-Month government bill rate	Datastream
Variance premium	VDAX decomposition	See Section 3

Source: ZEW stands for Zentrum für Europäische Wirtschaftsforschung, Mannheim, Germany; FRED stands for Federal Reserve Economic Data.

dent on the out-of-the-money (call or put) option at a given strike having a non-zero price (based on the mid-quote). The result is an estimate of the square root of implied variance across options of all strikes on the S&P 500. The same procedure is used by EUREX to calculate the VDAX. The implied volatility indices are calculated at an intraday frequency.

While the VIX obviously reflects stock market uncertainty, it conceptually must also harbor information about risk and risk aversion. Indeed, financial markets often view the VIX as a measure of risk aversion and fear in the market place. Because there are well-accepted techniques to measure the physical expected variance, the VIX can be split into a measure of stock market or economic uncertainty, and a residual that should be more closely associated with risk aversion. The difference between the squared VIX and an estimate of the conditional variance is typically called the variance premium (see, e.g., Carr and Wu, 2009). In Appendix A, we analyze a stylized example of a one-period discrete-state economy, for which we derive the implied and the expected physical variance of stock returns analytically. We use this example to illustrate how the VIX relates to risk preferences.

Empirically, to decompose the VIX index into the conditional variance and the variance premium, an estimate of the expected physical variance is needed. This estimate is customarily obtained by projecting future realized monthly variances onto a set of current instruments. We follow this approach using daily data on realized variances and the option-implied variance (as in, e.g., Bekaert and Hoerova, 2014). For Germany, the conditional physical variance is estimated using current realized variances at daily, weekly and monthly frequencies (see Corsi, 2009). For the United States, these variables are supplemented with the squared VIX. The equivalent procedure for Germany is infeasible because the realized variance and the VDAX are often very highly correlated. For the United States, we compute daily realized variances based on high-frequency (5-min) returns of the S&P 500 index. For Germany, we have realized variance estimates based on high-frequency (5-min) data starting in January 1996.[2] For the sample before January 1996, we use realized volatility estimates based on daily returns.

Expectations about the macroeconomic outlook are based on the ZEW Financial Market Survey (Zentrum für Europäische Wirtschaftsforschung, Mannheim, Germany). The survey polls about 350 financial market analysts every month on their expectations regarding the developments in each of the G7 countries. We extract information on macroeconomic uncertainty from the following question: In the medium-term (six months) the overall macroeconomic situation will: (1) Improve; (2) No Change; (3) Worsen. We have proportions of responses in each category for every month. To quantify these qualitative data, we follow the Carlson and Parkin (1975) method (see Appendix B for details).

Short-term interest rates are given by the 3-month T-bill for the US and the corresponding German government bill yield.[3] Credit spreads are given by the difference between BAA and AAA corporate yields for the US, and between corporate and government yields for Germany (the corporate bond market for Germany is much less developed compared to the United States so we use a public bond as a benchmark).

Fig. 1 plots the time series of the model inputs. The plots of the volatilities are dominated by three periods of turbulence, namely the collapse of LTCM in October 1998, the aftermath of the "irrational exuberance" in the early 2000s and the financial turmoil which started in the summer of 2007. Fig. 1 also shows that uncertainty about the US macroeconomic outlook rises sharply following the onset of the financial turmoil in August 2007. It reaches its sample high in March 2008. By contrast, while uncertainty about the German macroeconomic outlook has been rising since June 2007, its level remains well below the sample high recorded in January 1992, which reflects the aftermath of re-unification.

4. Empirical results

4.1. Parameter estimates

In estimating the model, we fix the scale of the unobserved fundamental uncertainty at 0.035, i.e. $\sigma_{uc} = 0.035$, for both countries. Table 2 presents the parameter estimates for Germany and the US, respectively. A number of results are notable.

First, we find relatively high persistence of the two unobservable series. In particular, the uncertainty processes in both countries are characterized by autocorrelation coefficients close to 0.90 and the effect of past shocks decays only slowly. The risk aversion process in Germany is much less persistent than that in the US and has more variable shocks. Yet, in both countries, market participants' attitude to risk contains a sizable predictable component.

Second, the estimated state variable dynamics reveal interesting relationships between risk aversion and macroeconomic uncertainty, on the one hand, and the short rate, on the other hand. We find that the US short-term rate is negatively related to uncertainty ($\gamma_2 < 0$). This is consistent with theory: in times of high uncertainty, investors desire to save more (precautionary savings effect) and so bond prices rise, while interest rates fall. In Germany, γ_2 is positive but small. The relation between risk aversion and the short-term rate (γ_1) is in theory subject to two offsetting effects: the aforementioned precautionary savings effect but also a utility smoothing effect. Higher risk aversion today leads to an expectation that future risk aversion will be relatively lower (due to stationarity). This induces a desire to borrow from the future, forcing down bond prices and raising interest rates (see Bekaert et al., 2009a). We find a negative relation between the risk aversion and the short-term rate for the US. Hence, the precautionary savings channel dominates the utility smoothing channel. In Germany,

[2] We use 5-min returns obtained from the Thomson Reuters Tick History to compute the realized variance for the 1996–1999 period. From January 2000 onwards, we use the realized variance data provided by Oxford-Man Institute Realized Library, version 0.2 (this data is also based on 5-min returns; see Heber et al., 2009, for details).

[3] The market for these securities in Germany is less liquid than the US T-bill market, but it is important to keep the rates comparable in terms of (lack of) default risk.

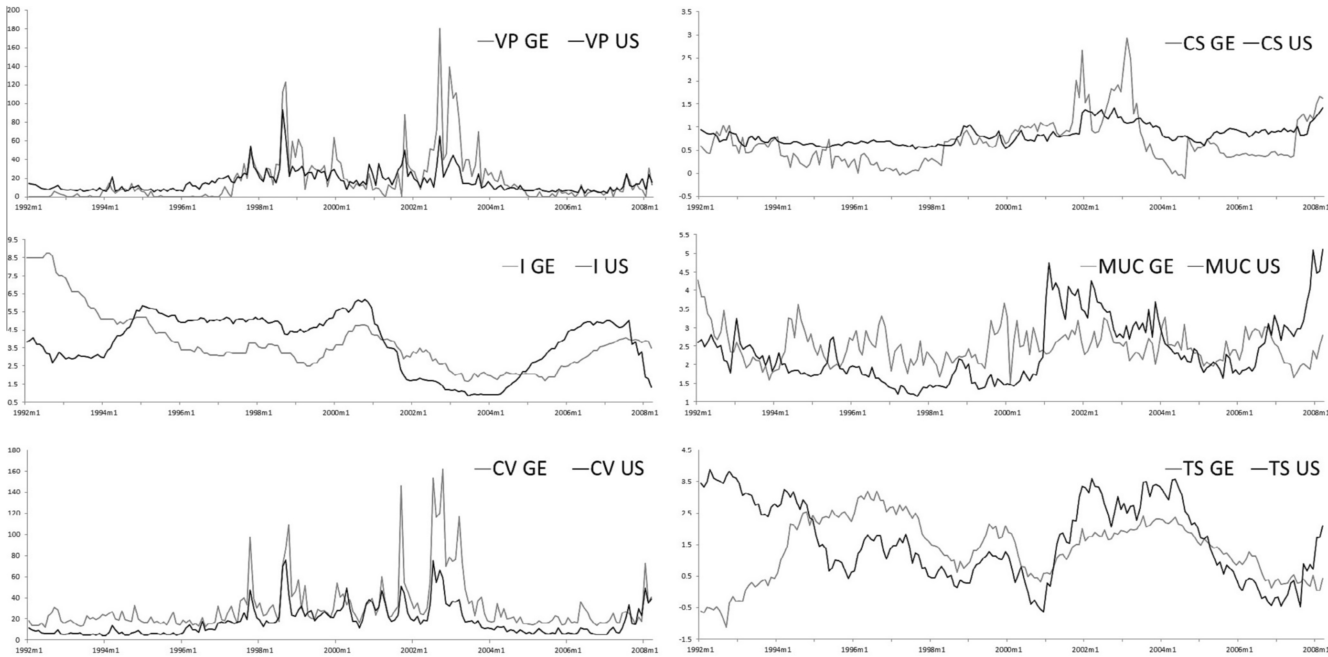

Fig. 1. Plots of model inputs for the US (*US*) and Germany (*GE*) (variance premium, VP; credit spread, CS; 3-month rate, I; survey uncertainty, MUC; conditional variance, CV; term spread, TS).

the two effects offset each other, and the coefficient is essentially zero.

Of course, such effects can also be interpreted as flight-to-quality effects. When risk aversion increases, investors desire to shift from stocks to bonds. This desired rebalancing of investors' positions leads to a rise in bond prices and a fall in the short-term interest rates. Such a phenomenon has been observed during episodes of severe financial market stress such as the LTCM collapse in October 1998 or the recent financial crisis.

Finally, we discuss the elements in B_y. Credit spreads are statistically significantly and positively related to uncertainty. In the US, the are also negatively related to the interest rate. The variance premium, which is assumed to move one for one with risk aversion, loads negatively on uncertainty in the US but positively in Germany; however the coefficients are insignificantly different from zero for both countries.

The conditional variance is positively related to both uncertainty and risk aversion, with uncertainty (risk aversion) link stronger in Germany (the US). The relation with the interest rate is not significant. The term spread is negatively related to all three state variables.

4.2. Time series behavior

Our main output are estimates of the risk aversion and uncertainty series for Germany and the US, which we plot in Figs. 2 and 3. Risk aversion is expressed as a deviation from the sample average (set equal to 100) and uncertainty is re-scaled to match annualized GDP volatility on average.

The time series plots of risk aversion (Fig. 2) are dominated by several periods of turbulence: (1) the Asian crisis in the second half of 1997; (2) the collapse of LTCM in October 1998; (3) market turbulence following the 9/11 terrorist attacks; (4) the aftermath of the "irrational exuberance" and period of accounting uncertainties with a peak in 2002–2003; and (4) the credit market turmoil (since summer 2007). The risk aversion series for Germany recorded its sample high in September 2002, in the aftermath of the irrational exuberance episode, and its sample low in the middle of the 1990s (February 1996). For the US, the sample high of the risk aversion series was during the LTCM crisis (August 1998) and its sample low was in January 2007 (high risk appetite just before the financial turmoil erupted) later on that year. Risk aversion estimates for the US and Germany are positively correlated, with a correlation equal to 0.65.

Investigating the behavior of the risk aversion estimates during the 2007–2008 market turmoil is of obvious interest. The market turmoil started in summer 2007 in the US subprime market. A market-wide reassessment of risk led to sharp increases in credit spreads across all segments of the credit market. The rapidly falling market values of credit instruments reduced both the capital as well as the profitability of the banking system and investors embarked on a "flight to safety". One illustration of the intensity of the subprime turmoil is the collapse of Bear Stearns, a major US investment bank, in March 2008. In this episode, the risk aversion series show similar but not equal increases for the US and for Germany. Risk aversion increases more in the US as compared to Germany since the impact of the subprime turmoil was more immediate for the US.

The time series plots of uncertainty (Fig. 3) exhibit business cycle-like variation (we discuss correlations with business cycle variables in the next Section). The uncertainty series for Germany recorded its sample high in February 2003 and its sample low in August 2004. For the US, the sample high of the uncertainty series was in March 2008 and its sample low in March 1993. It is interesting to note that the highest recorded value of uncertainty for the US is in March 2008, the last data point of our sample. This reflects the effects of the credit market turmoil. Uncertainty estimates for Germany are positively correlated with the US uncertainty estimates, with a correlation equal to 0.55. This is consistent with the international business cycles literature that documents the large international impact of US shocks.[4]

The B_y^{-1} matrix reveals how risk aversion and uncertainty load on the three observed series (the credit spread, variance premium,

[4] See, e.g., Canova and Marrinan (1998). Eickmeier (2007) also finds an increased comovement between the German and US confidence measures, particularly since the end of the 1990s.

Table 2
Main results.

Parameters	USA	Germany
ϕ_{uc}	0.9016*** (21.337)	0.8791** (34.169)
ϕ_{ra}	0.8796*** (24.913)	0.4500** (10.149)
ϕ_i	0.9581*** (86.916)	0.9699*** (99.308)
ϕ_{muc}	0.8321*** (20.167)	0.6390* (10.301)
σ_{ra}	0.5966*** (45.972)	1.3303*** (42.233)
σ_i	0.1771*** (64.892)	0.1651*** (43.575)
σ_{muc}	0.3590*** (64.945)	0.3811*** (41.888)
B^{uc}_{cs}	0.1943*** (19.719)	0.6439*** (23.640)
B^{ra}_{cs}	0.0025 (0.924)	−0.0009 (−0.464)
B^{i}_{cs}	−0.0441*** (−2.902)	0.0015 (0.027)
B^{uc}_{vp}	−0.6348 (−0.414)	6.4889 (0.762)
γ_1	−0.0057* (−2.292)	−0.0008 (−1.065)
γ_2	−0.0336*** (−8.715)	0.0143** (2.029)
B^{uc}_{ts}	−0.3859*** (−4.651)	−0.3377*** (−4.326)
B^{ra}_{ts}	−0.0118 (−0.661)	−0.0013 (0.0043)
B^{i}_{ts}	−0.6434*** (−9.979)	−0.3745*** (−5.264)
σ_{ts}	0.0662*** (17.682)	0.0588*** (13.101)
B^{uc}_{cv}	0.9164 (0.639)	5.4933*** (8.467)
B^{ra}_{cv}	0.9002*** (23.960)	0.0206 (2.439)
B^{i}_{cv}	0.1718 (0.977)	−0.6091 (−0.915)
σ_{cv}	0.2238*** (19.886)	0.5053*** (21.585)

Note: The two models are estimated by maximum likelihood, using 195 monthly observations. The *t*-statistics, repeated in parentheses, are based on White (1980) standard errors, which are robust to heteroskedasticity and distributional misspecification.
***,**,* denote significance at the 0.01, 0.05 and 0.10-level.

and the short-term rate). We report these loadings in Table 3. Risk aversion loads positively on the credit spread and on the variance premium. This is consistent with the common perception that credit spreads and the variance premium can serve as indicators of investors' risk attitude. However, for Germany, risk aversion loads negatively, but not significantly, on the credit spread. Uncertainty loads positively on the credit spread and almost zero on variance premium in both countries. It indicates that variance premium has become primarily an indicator of risk aversion and, unlike credit spreads, does not contain much information on uncertainty. This is consistent with Beber and Brandt (2009) who find no evidence of a relationship between macroeconomic uncertainty and trading activity in stock index options.

4.3. Granger causality results

Table 4 reports Granger causality tests. We find strong overall Granger causality in the equations for uncertainty in the US, and for both risk aversion and uncertainty in Germany (significance at the 5% level). The strongest relations are US risk aversion predicting or anticipating German risk aversion, and between US and German uncertainties in both directions (all significant at the 1% level). In Germany, there is also a Granger causality relation between risk aversion and uncertainty, significant at the 10% level in both directions. US risk aversion is best described by a pure autoregressive process, with no significant Granger causality present.

5. Validating the risk and uncertainty measures

In this section, we first validate and analyze our risk aversion and uncertainty measures by comparing them to alternative estimates in the extant literature. We then further explore links between our measures and (a) the business cycle (b) financial stress indices (c) disagreement indices and (d) liquidity indices. As indicated before, a number of prominent asset pricing models have formally linked risk aversion to the stage of the business cycle (Campbell and Cochrane, 1999). There also is general consensus that people are more risk tolerant when wealthier. This only has repercussions for asset prices and risk premiums when wealth changes at the aggregate level, and the business cycle may capture such aggregate changes in wealth (Sharpe, 1990). Moreover, there is a recent literature that suggests that uncertainty (shocks) is (are) associated with future downturns (Bloom, 2009; Stock and Watson, 2012; Bekaert and Hoerova, 2014). Allen et al. (2012) show that uncertainty in the financial sector predicts future economic downturns. A large finance literature suggests macroeconomic uncertainty is priced in stock returns (see, e.g, Bali et al., 2015; Anderson et al., 2009). The recent global financial crisis has also rekindled interest in financial stress indices. Financial stress may reflect macro-economic and/or Knightian uncertainty but also relate to increases in risk aversion, which may manifest itself in, for example, the tightening of leverage constraints by financial institutions and portfolio managers, stricter limits on risky positions, etc. Finally, there is a voluminous literature on the pricing of disagreement and liquidity in asset prices, e.g., Bali et al. (2014) and Diether et al. (2002).

5.1. Validating the risk aversion measure

Table 5 documents the correlation between our risk aversion measure and two widely used practitioner's indices of risk attitude, the JP Morgan G10 Risk Tolerance Index (*RTI*) and the Credit Suisse First Boston Risk Appetite Index (*RAI*). Both measures use global financial data, although with a US bias. The RTI uses a limited number of financial variables combining liquidity risk, credit risk and financial market volatility to arrive at a risk aversion index; the RAI uses bond and equity returns and volatility in 64 countries to construct a risk *appetite* index (note, therefore, that we expect correlations between RAI and our risk aversion measures to be negative). As Table 5 reveals, all correlations are statistically significant and have the expected sign but the correlation coefficients are higher for the US measure compared to the German measure. Given the US focused nature of the indices, this is not surprising.

As indicated before, the variance premium is more and more accepted as a risk aversion indicator in the finance literature (see also Appendix A for further economic motivation). Table 5 also reports the correlation between our measures and various measures of the variance risk premium. Of course, we used the variance

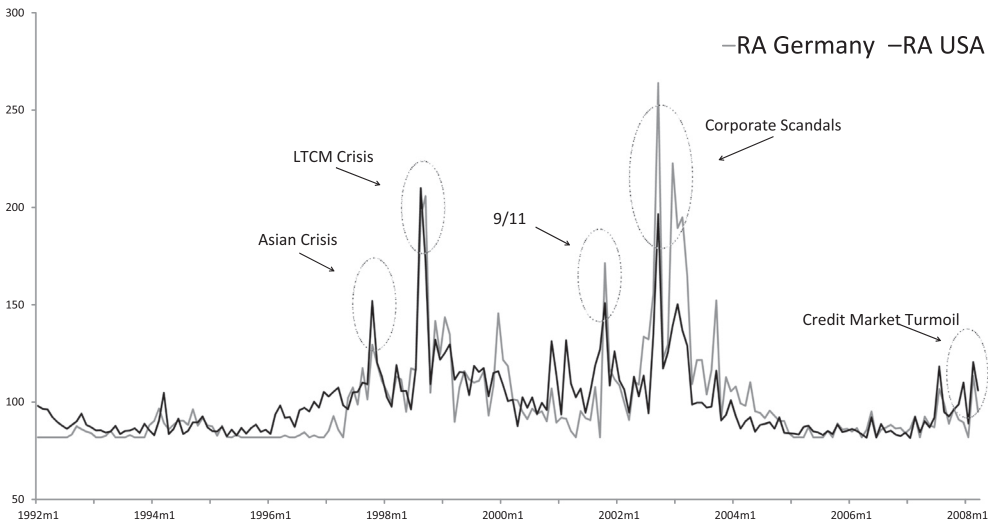

Fig. 2. Time series of risk aversion RA (mean set to 100).

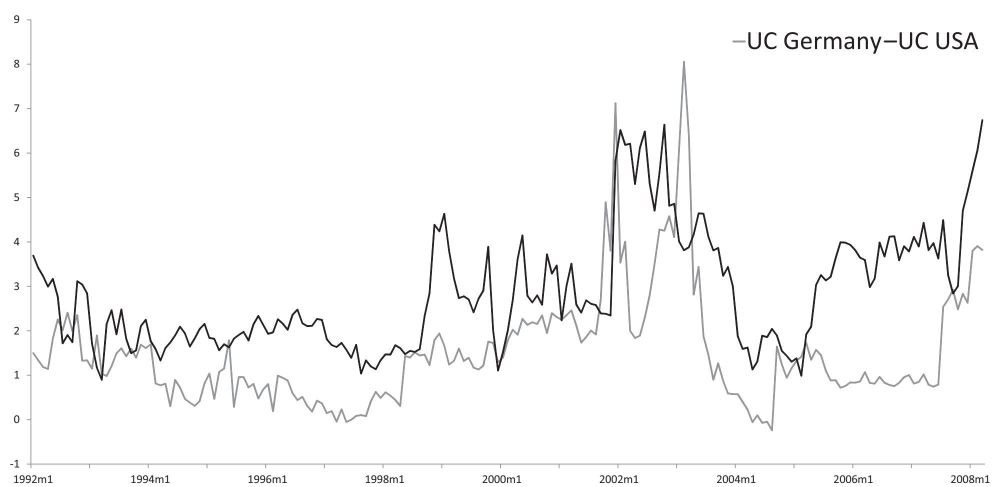

Fig. 3. Time series of uncertainty UC (scaled by the GDP volatility).

Table 3
Loadings of risk aversion and uncertainty.

B_y^{-1} elements	USA	Germany
B_{uc}^{cs}	5.1048***	1.5389***
	(22.546)	(23.179)
B_{uc}^{vp}	−0.0126	0.0014
	(−0.926)	(0.468)
B_{uc}^{i}	0.2249**	−0.0023
	(2.790)	(−0.023)
B_{ra}^{cs}	3.2404	−9.9861
	(0.414)	(−0.769)
B_{ra}^{vp}	0.9920***	0.9910***
	(37.112)	(33.988)
B_{ra}^{i}	0.1428	0.0152
	(0.409)	(0.027)

Note: Estimates of the matrix $[B_y^1]^{-1}$ (see below). The standard errors are computed using the delta method.

$$\left[B_y^1\right]^{-1} = \begin{bmatrix} B_{uc}^{cs} & B_{uc}^{vp} & B_{uc}^{i} & 0 \\ B_{ra}^{cs} & B_{ra}^{vp} & B_{ra}^{i} & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

***,**,* denote significance at the 0.01, 0.05 and 0.10-level.

Table 4
Granger causality results.

	RA_t^{US}	UC_t^{US}	RA_t^{GE}	UC_t^{GE}	All
RA_{t+1}^{US}		0.2188	0.9881	0.1078	1.6403
		(0.640)	(0.320)	(0.740)	(0.650)
UC_{t+1}^{US}	0.2771		0.6121	7.0437	10.6100
	(0.599)		(0.434)	(0.008)	(0.014)
RA_{t+1}^{GE}	9.2214	0.1225		3.4442	9.7084
	(0.002)	(0.726)		(0.063)	(0.021)
UC_{t+1}^{GE}	1.4370	8.6834	3.3990		9.9350
	(0.231)	(0.003)	(0.065)		(0.019)

Note. Granger causality test results for the US (superscript *US*) and German (superscript *GE*) risk aversion and uncertainty series (VAR with 1 lag, selected by the Akaike information criterion). Each row represents one equation, with the variable in the column being excluded. The table reports χ^2 statistic, with *p*-values in parentheses.

premium measure as computed in Bekaert and Hoerova (2014) as an input in our estimation, so a high correlation is to be expected. That measure is 99% correlated with our risk aversion measure in the US. For the German equivalent, the correlation with the

Table 5
Validating the risk aversion measure.

	RA_t^{US}	RA_t^{GE}
RTI	0.4451 (<0.0001)	0.2443 (0.0065)
RAI	−0.4626 (<0.0001)	−0.1548 (0.0307)
VP_{BH}^{US}	0.9961 (<0.0001)	0.6742 (<0.0001)
VP_{BH}^{GE}	0.8100 (<0.0001)	0.7681 (<0.0001)
VP_{BTZ}^{US}	0.8139 (<0.0001)	0.6774 (<0.0001)
RA_{CC}	−0.3008 (0.0157)	−0.2783 (0.0260)
$Sent_{BW}$	0.2444 (0.0006)	−0.1074 (0.1349)
MCSI	0.2036 (0.0043)	0.4212 (<0.0001)
GFK_{BC}	0.0725 (0.3137)	0.0404 (0.5751)
GFK_{IN}	0.3948 (<0.0001)	0.2225 (0.0018)
GFK_{WS}	0.1535 (0.0321)	0.1824 (0.0107)
CCI_{OECD}^{US}	0.2180 (0.0022)	0.4358 (<0.0001)
CCI_{OECD}^{GE}	0.2258 (0.0015)	0.0694 (0.3350)

Note. Correlations between the risk aversion measures for the US (superscript *US*) and Germany (superscript *GE*) and other risk attitude indicators (p-values in parentheses): JP Morgan G10 Risk Tolerance Index (*RTI*); Credit Suisse First Boston Risk Appetite Index (*RAI*), variance premium measures based on Bekaert and Hoerova (2014) (VP_{BH}) and Bollerslev et al. (2009) (VP_{BTZ}); risk aversion based on Campbell and Cochrane (1999) (RA_{CC}); sentiment indicator based on Baker and Wurgler (2007) ($Sent_{BW}$); US Michigan consumer sentiment indicator (*MCSI*); German Gfk consumer sentiment indicator for business cycle (GFK_{BC}), income (GFK_{IN}) and willingness to spend (GFK_{WS}); OECD consumer confidence indicators (*CCI*).

German risk aversion measure is 77%. For the US, we also computed the Bollerslev et al. (2009) variance premium measure, which subtracts the realized monthly variance from the squared VIX to arrive at the variance premium. This measure is 81% correlated with risk aversion in the US and 68% correlated with risk aversion in Germany. In fact, the cross-correlations between variance premiums in one country and our risk aversion measure in the other country are quite high, indicating a global component in risk aversion.

The changes in risk aversion that are reflected in financial asset prices could have a variety of economic sources. First, in external habit models such as Campbell and Cochrane (1999) (logarithmic) risk aversion is a negative affine function of the log "consumption surplus ratio," which in turn is aggregate consumption minus the "habit stock" divided by consumption. As aggregate consumption moves closer to the habit stock (as would happen in recessions), aggregate risk aversion increases. Campbell and Cochrane (1999) model the surplus ratio as a heteroskedastic autoregressive process, with its shocks perfectly correlated with consumption shocks. We use the Campbell and Cochrane measure (RA_{CC}) created from data on US nondurables and services consumption growth in Bekaert and Engstrom (2010). While the resulting measure is clearly counter-cyclical, Table 5 reveals that it has the wrong correlation with our risk aversion measure. The correlation should be positive but it is negative. Clearly, our measure is dominated by movements that cannot be captured by a slow-moving risk aversion measure extracted from purely economic data. This result suggests that the asset pricing literature should accommodate "non-fundamental" changes in risk aversion, as foreshadowed in Gordon and St-Amour (2004) and Bekaert et al. (2010).

Second, the behavioral finance literature suggests that the sentiment of retail investors may drive asset prices and cause non-fundamental price swings. One of the best known sentiment indices builds on the work by Baker and Wurgler (2007), and we use their sentiment index ($Sent_{BW}$), which is extracted from data on trading volume (NYSE turnover); the dividend premium; the closed-end fund discount; the number and first-day returns on IPOs; and the equity share in new issues. High values mean positive sentiment and thus we expect a negative correlation with our risk aversion measures. Table A shows that the correlation is positive and significant for the US and negative but insignificant for Germany. We conclude that the sentiment index does not capture risk aversion changes. This remains true when we use the version of the index that controls for macroeconomic conditions (not reported).

Because the Baker–Wurgler index relies on financial data, it may not directly reflect the sentiment of investors. Lemmon and Portnaiguina (2006) and Qiu and Welch (2006) therefore suggest to use a consumer sentiment index, and propose to use the Michigan Consumer Sentiment Index (*MCSI*). High values of this index indicate that consumers are optimistic, so we expect negative correlations. Again, the results disappoint as the correlations have the wrong sign. For Germany, we use the Gfk indicator, based on a monthly survey of about 2000 consumers, asking them about (1) their expectations about the business cycle (GFK_{BC}); (2) their income (GFK_{IN}) and (3) their willingness to spend (GFK_{WS}). For all three measures, unfortunately, the correlations have the wrong sign. The OECD also produces a consumer confidence indicators (CCI_{OECD}) for the member countries, based on households' plans for major purchases and their economic situation, both currently and their expectations for the immediate future. Constructed in the same way as the indices considered above, we expect negative correlations with our measures but correlations are positive instead, in both Germany and the US.

Because the surveys reflect consumer's attitudes regarding current and future economic conditions, they may correlate with uncertainty rather than with risk aversion, and we verify this conjecture in the next section.

5.2. Validating the uncertainty measure

In a number of asset pricing models, aggregate risk premiums are linked to economic uncertainty (see e.g. Bansal et al., 2005; Bekaert et al., 2009a). Bali and Zhou (2012) also investigate the pricing of economic uncertainty in the cross-section. The most obvious direct measure of economic uncertainty would be a time-series estimate of the conditional variance of economic activity measures. The disadvantage of such measures is that the frequency at which economic data are available is typically low, impairing the precision of such conditional variance estimates.

In Table 6, we use, following Bali and Zhou (2012), the conditional variance of the Chicago Fed National Activity Index (CV_{CFNAI}) and the conditional variance of industrial production in both the US and Germany (CV_{IP}). The conditional variances are based on a GARCH(1,1) model. The correlations between our uncertainty measures and the industrial production variances are insignificant, but the correlation with the conditional variance of the CFNAI index is positive and significant for both Germany and the US, with the correlation for Germany being surprisingly higher and more significant than the correlation for the US.

Table 6
Validating the uncertainty measure.

	UC_t^{US}	UC_t^{GE}
CV_{CFNAI}	0.1069 (0.0890)	0.3961 (<0.0001)
CV_{IP}^{US}	0.0191 (0.7912)	0.0077 (0.9901)
CV_{IP}^{GE}	−0.1075 (0.1349)	−0.0507 (0.4818)
MUC_{JLN}^{1m}	0.5254 (<0.0001)	0.4793 (<0.0001)
MUC_{JLN}^{3m}	0.5395 (<0.0001)	0.4926 (<0.0001)
MUC_{JLN}^{12m}	0.5518 (<0.0001)	0.5052 (<0.0001)
PUC_{BBD}^{US}	0.1620 (0.0237)	0.5751 (<0.0001)
PUC_{BBD}^{GE}	0.2648 (0.0019)	0.5468 (<0.0001)
$Sent_{BW}$	−0.0025 (0.9728)	0.1403 (0.0504)
$MCSI$	−0.3259 (<0.0001)	−0.2660 (0.0002)
GFK_{BC}	0.2320 (0.0011)	0.0344 (0.6327)
GFK_{IN}	0.0725 (0.3141)	0.1368 (0.0565)
GFK_{WS}	−0.0194 (0.7883)	−0.0879 (0.2217)
CCI_{OECD}^{US}	−0.3466 (<0.0001)	−0.2699 (0.0001)
CCI_{OECD}^{GE}	0.2793 (<0.0001)	0.1495 (0.0370)
CV_{BHL}^{US}	0.3189 (<0.0001)	0.5443 (<0.0001)
CV_{BHL}^{GE}	0.3222 (<0.0001)	0.5485 (<0.0001)
CV_{BTZ}^{US}	0.3879 (<0.0001)	0.5188 (<0.0001)

Note: Correlations between the uncertainty measures for the US (superscript *US*) and Germany (superscript *GE*) and other uncertainty indicators (*p*-values in parentheses): conditional variance of the Chicago Fed National Activity Index (CV_{CFNAI}); conditional variance of the industrial production (CV_{IP}); macroeconomic uncertainty measures based on Jurado, Ludvigson and Ng (2015) for 1-, 3- and 12-month forecasting horizons (MUC_{JLN}); policy uncertainty index based on Baker, Bloom and Davis (2013) (PUC_{BBD}); conditional stock market variance measures based on Bekaert and Hoerova (2014) (CV_{BH}) and Bollerslev et al. (2009) (CV_{BTZ}); the other indicators are as in Table 5.

One way to reduce noise is to combine information from many indices. This is exactly what Jurado et al. (2015) do. Their uncertainty measure is defined as a weighted sum of the conditional volatilities of 132 financial and macroeconomic series, with the bulk of the series being macroeconomic. The data are mostly global or US related. The estimated time series is highly persistent and it is strongly countercyclical, spiking in the months surrounding the 1974–1975 and 1981–1982 recessions and the Great Recession of 2007–2009. In Table 6, we show correlations with three variants of the Jurado et al. (2015) measure, corresponding to different forecasting horizons of 1, 3, and 12 months (MUC_{JLN}^{1m} etc.). The correlations have the expected sign, are in the 0.5 range, and strongly statistically significant. Interestingly, the MUC_{JLN} measures are much less strongly correlated with our risk aversion measure (not reported, but the correlations are all below 0.3) showing that our uncertainty and risk aversion measures do reflect different economic concepts.

Macroeconomic uncertainty may be correlated with political uncertainty, which has recently been proposed as a source of asset risk premiums (see e.g. Pastor and Veronesi, 2013). Baker et al. (2013) create a policy uncertainty index (which, however, also uses information on disagreement among economic forecasters, see below) for the US, which we use in our correlation analysis (PUC_{BBD}). The index exists for both the US and for Germany (although the German series only starts in 1997) and data were obtained from Bloom's web site. The policy uncertainty indices, both the US and German versions, correlate more strongly with our German uncertainty series than with the US uncertainty series. While surprising, it is conceivable that uncertainty is generated partially by global economic factors that are particularly relevant for a strongly open economy such as Germany's. Below, we show that part of this high correlation may be due to the disagreement component in the Policy uncertainty index.

Macroeconomic uncertainty may be correlated with consumer sentiment. We therefore also report correlations with the sentiment indices examined before. For the US Michigan Consumer Sentiment Index (*MCSI*), we now get the expected negative correlation between consumer optimism and uncertainty, with highly statistically significant correlations of around 30% for both the US and German uncertainty series. For the German Gfk indicator, correlations are mostly positive not statistically significant, and only have the expected negative sign in the case of the indicator of the consumer willingness to spend, GFK_{WS}. For the OECD indicators, we get statistically significant negative correlations of about 30% for the US indicator, CCI_{OECD}^{US}, but positive correlations for the corresponding German indicator.

Finally, Table 6 shows the correlation between our uncertainty measure and the conditional variance of stock returns in the US and Germany. We use our projection measure following Bekaert and Hoerova (2014), where the realized variances computed from high frequency returns are projected on the past realized variances and the VIX (for Germany, we omit the VIX as in Corsi, 2009). We also show results for the conditional variance computed using the martingale model in Bollerslev et al. (2009). The correlations vary between 32% and 39% for the US uncertainty series, and between 52% and 55% for the German uncertainty series, and are always highly statistically significant.

We conclude that our uncertainty measures are significantly and substantially correlated with both stock market uncertainty and with macroeconomic uncertainty from a variety of economic time series as in Jurado et al. (2015).

5.3. Risk aversion, uncertainty and the business cycle

As indicated above, a number of theories suggest countercyclical behavior of risk aversion and uncertainty. We now verify this conjecture. For the US, we use two well-known indices that measure, respectively, economic and financial conditions for the Chicago Fed, the Chicago Fed National Activity Index (CFNAI), and the Chicago Fed National Financial Conditions Index (NFCI). The CFNAI is increasing in economic growth, whereas positive (negative) values of the NFCI indicate financial conditions that are tighter (looser) than average. Table 7 reports the correlations. The correlations have, with one exception, the right sign in that both better economic conditions and better financial conditions are associated with lower risk aversion and uncertainty. For economic conditions, we, however, find that it is primarily uncertainty, not risk aversion that is countercyclical. In fact, the correlation with

Table 7
Risk aversion, uncertainty and the business cycle.

	RA_t^{US}	RA_t^{GE}	UC_t^{US}	UC_t^{GE}
CFNAI	−0.1732	0.1675	−0.3344	−0.4754
	(0.1272)	(0.0192)	(<0.0001)	(<0.0001)
NFCI	0.5711	0.2136	0.3891	0.5017
	(<0.0001)	(0.0027)	(<0.0001)	(<0.0001)
IFO_{BC}	−0.0995	0.0902	0.0968	−0.2175
	(0.1665)	(0.2100)	(0.1784)	(0.0023)
IFO_{BS}	−0.0507	0.0321	0.1680	−0.0954
	(0.4819)	(0.6556)	(0.0189)	(0.1846)
IFO_{BE}	−0.1630	−0.1656	−0.0456	−0.3747
	(0.0228)	(0.0207)	(0.5271)	(<0.0001)
BOS_F	−0.1133	−0.0937	0.1006	0.1416
	(0.1147)	(0.1924)	(0.0066)	(0.0484)
BOS_C	−0.3200	0.0873	−0.3300	−0.4406
	(<0.0001)	(0.2248)	(<0.0001)	(<0.0001)

Note: Correlations between the risk aversion and uncertainty measures for the US (superscript *US*) and Germany (superscript *GE*) and business cycle measures (*p*-values in parentheses): the Chicago Fed National Activity Index (*CFNAI*); the Chicago Fed National Financial Conditions Index (*NFCI*); "balance" indicators (difference between proportions of optimistic versus pessimistic respondent) based on the German Ifo Business Climate survey for business climate (IFO_{BC}), business situation (IFO_{BS}) and business expectations (IFO_{BE}); "balance" indicators (difference between proportions of optimistic versus pessimistic respondent) based on the US Business Outlook survey for future business conditions (BOS_F) and current business conditions (BOS_C).

US risk aversion fails to be significant and the one with German risk aversion has the wrong sign. Tight financial conditions are associated with both high risk aversion and substantial economic uncertainty.

In addition to using economic activity indices, we also collected survey information on the business cycle. For Germany, the Ifo Business Climate Indicator surveys German manufacturing firms and is a widely followed indicator of business conditions. The main indicator, called "Business Climate" (IFO_{BC}), combines two sub-indicators, "Business Situation" (IFO_{BS}) and "Business Expectations" (IFO_{BE}), with the first reflecting current conditions, the second looking forward. For all three categories, there is a level indicator and a "balance" indicator, representing the difference between proportions of optimistic versus pessimistic respondents. We only report the correlations with the "balance" indicators, as the correlations with the level index were very similar. High values of the index indicate good conditions, so we expect negative correlations to indicate countercyclicality. Table 7 reveals that the correlations are negative, and statistically significant (except for the business situation indicator), for our German uncertainty measure, indicating it is countercyclical. For the US uncertainty measures the correlations have the wrong sign or are insignificant. For the risk aversion measures, we only find statistically significant negative correlations with the expectations measure, for both the US and Germany. The strongest negative correlation is, as should be expected, between the Expectations indicator and our German macroeconomic uncertainty measure.

For the US, we use the equivalent survey of manufacturing firms, the Manufacturing Business Outlook Survey compiled by the Federal Reserve Bank of Philadelphia. Table 7 reports correlations with the two "balance" indicators, one referring to business conditions in the future (six months from now), BOS_F, and the other referring to business conditions currently (for the next month), BOS_C. We find strong negative correlations with current business conditions for both risk aversion and uncertainty series in the US (correlations of 32% and 33%, respectively), and for the German uncertainty series (a negative correlation of 44%). Correlations with business conditions six months from now are statistically insignificant or have the wrong sign.

5.4. Risk aversion, uncertainty and financial stress

As the global financial crisis deepened, the literature on financial stress and systemic risk proliferated. We collected a number of well-known stress indices: the Kansas City Financial Stability Index, *Kansas* (see Hakkio and Keeton, 2009; and the Data Appendix for details), the ECB's Composite Index of Systemic Stress (CISS), based on either European Monetary Union data ($CISS^{EMU}$) or US data ($CISS^{US}$) (see Holló et al., 2012) and the IMF Financial Stress Index for the US and Germany, IMF^{US} and IMF^{GE} (see Balakrishnan et al., 2009). These indices combine price, spread and volatility information in various ways. The Kansas index does include the VIX index; the CISS indices use some quantity information as well, whereas the IMF index includes information from the TED spread.

As Table 8 shows, generally, the correlations with both uncertainty and risk aversion are high and statistically significant. For example, for German uncertainty, the first three of the five indices show a higher than 0.60 correlation, even the Kansas index which is based on US data. For the US uncertainty, the correlations with the three indices are marginally lower, around 0.50 on average. By contrast, the US risk aversion series shows much higher correlations with the three indices than the German risk aversion series, even for the $CISS^{EMU}$ indicator which is based on the European data. The IMF financial stress index for the US shows the highest correlation with US risk aversion (47%) while the corresponding index for Germany has the highest correlation, 72%, with German uncertainty. It should not be surprising that financial stress indices move in line with our measures of risk aversion and uncertainty.

A number of recent articles have attempted to identify flights-to-safety or quality, in which stress periods in financial markets cause sharp (downward) price movements in the equity market, but sharp upward movements in the price of the liquid

Table 8
Risk aversion, uncertainty and financial stress.

	RA_t^{US}	RA_t^{GE}	UC_t^{US}	UC_t^{GE}
Kansas	0.6764	0.2305	0.4713	0.6630
	(<0.0001)	(0.0012)	(<0.0001)	(<0.0001)
$CISS^{US}$	0.5604	0.2003	0.5853	0.6140
	(<0.0001)	(0.0050)	(<0.0001)	(<0.0001)
$CISS^{EMU}$	0.4007	0.0049	0.5304	0.6182
	(<0.0001)	(0.9458)	(<0.0001)	(<0.0001)
IMF^{US}	0.4685	0.2133	0.2693	0.3279
	(<0.0001)	(0.0028)	(<0.0001)	(<0.0001)
IMF^{GE}	0.4691	0.0424	0.3855	0.7180
	(<0.0001)	(0.5562)	(<0.0001)	(<0.0001)
FTQ	0.9641	0.6085	0.2321	0.5337
	(<0.0001)	(<0.0001)	(0.0011)	(<0.0001)
FTS^{US}	0.5650	0.2615	0.3029	0.3763
	(<0.0001)	(0.0002)	(<0.0001)	(<0.0001)
FTS^{GE}	0.7110	0.4000	0.3139	0.5342
	(0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

Note: Correlations between the risk aversion and uncertainty measures for the US (superscript *US*) and Germany (superscript *GE*) and financial stress measures (*p*-values in parentheses): the Kansas City Financial Stability Index (*Kansas*); the Composite Index of Systemic Stress based on the US and European Monetary Union, EMU, data (*CISS*); the IMF Financial Stress Index (*IMF*); flight-to-quality measures based on Mueller et al. (2012) (*FTQ*); flight-to-safety measure based on Baele et al. (2013) (*FTS*).

benchmark bond. Mueller et al. (2012) create a measure by essentially comparing implied volatility in the equity market to that of the bond market. They measure implied volatility in the Treasuries market, TIV, as a square root of the one-month implied variance for futures on 30-year Treasuries. Their indicator for a flight-to-quality (*FTQ*) is then the difference between the VIX, indicating stress in the less liquid equity market, and the TIV, indicating, potentially, high liquidity and low volatility in the bond market. The measure is very highly correlated with the US risk aversion measure, but less correlated with the US uncertainty measure, although for Germany this correlation remains quite high, at around 50%. Baele et al. (2013) extract a flight-to-safety dummy from bond and stock returns and a variety of models indicating flight-to-safety like behavior. Their measure is available for both the US and Germany (FTS^{US} and FTS^{GE}, respectively). The *FTS* measure for the US correlates strongly with the US risk aversion (0.57) and US uncertainty (0.30). Correlations with German risk aversion and uncertainty series are also relatively high. The *FTS* measure for Germany shows the highest correlation with the US risk aversion (0.71), followed by German uncertainty (0.53) and German risk aversion (0.40). Here, the German risk aversion is indeed more highly correlated with the German *FTS* indicator than with the US *FTS* indicator, whereas this was surprisingly not the case for the CISS and IMF indices.

One feature that is again apparent from these results is that there are clearly global components in uncertainty and risk aversion, with the German series correlating strongly with US stress indices and vice versa.

5.5. Risk aversion, uncertainty and disagreement

A number of recent papers have examined the link between asset risk premiums and dispersion measures of the forecasters of economic variables such as inflation and GDP growth. Such dispersion may stem from differences of opinion, but it may also be correlated with aggregate macroeconomic uncertainty.

In Table 9, we show correlations with dispersion measures based on the Blue Chip Economic Indicator forecast data for the US. These measures are cross sectional standard deviations of the forecasts for the CPI (BC_{CPI}) and for real GDP (BC_{GDP}). As could be expected, these measures indeed correlate more highly with the US uncertainty series than with the US risk aversion series but they are nonetheless statistically significant in every case. The German uncertainty series also correlates quite highly with US GDP forecast dispersion. We also use the GDP forecast dispersion from the Survey of Professional Forecasters as constructed in Bekaert and Engstrom (2010), *SPF*. This measure correlates more highly with risk aversion than with uncertainty for the US series.

Table 9
Risk aversion, uncertainty and disagreement.

	RA_t^{US}	RA_t^{GE}	UC_t^{US}	UC_t^{GE}
BC_{CPI}	0.1556	0.1715	0.4200	0.2095
	(0.0299)	(0.0165)	(<0.0001)	(0.0033)
BC_{GDP}	0.2513	−0.0594	0.3454	0.4984
	(0.0004)	(0.4095)	(0.0001)	(<0.0001)
SPF	0.5597	0.2929	0.3052	0.5086
	(<0.0001)	(0.0188)	(0.0142)	(<0.0001)

Note: Correlations between the risk aversion and uncertainty measures for the US (superscript *US*) and Germany (superscript *GE*) and disagreement measures (*p*-values in parentheses): forecast dispersion based on the US Blue Chip Economic Indicator forecast data for the CPI (BC_{CPI}) and for real GDP (BC_{GDP}); forecast dispersion for the US Survey of Professional Forecasters (*SPF*).

Disagreement appears to be highly positively correlated with both risk aversion and macroeconomic uncertainty. It therefore should not be surprising that it has information about asset risk premiums.

5.6. Risk aversion, uncertainty and liquidity

The asset pricing literature has long recognized that liquidity may be priced and a variety of liquidity indicators have been used in asset pricing models. However, volatility and liquidity are intricately linked and so periods of extreme illiquidity may coincide with periods of high risk aversion and/or uncertainty. We collected a number of liquidity indicators to verify this conjecture.

In Table 10, we show correlations with liquidity measures. We collected four measures. The first measure is the Bond Liquidity Factor from Fontaine and Garcia (2012), BLF_{FG}, which derives liquidity premia computed from price differentials between pairs of U.S. Treasury securities, where each pair has similar cash flows but different ages. This liquidity premium is low in crisis times and we therefore expect negative correlations with our risk aversion and uncertainty measures. The second and third indicators are based on Pastor and Stambaugh (2003) measures of levels and innovations in stock market liquidity. The liquidity level measure, PS_{LEVEL}, is the equally weighted average of the liquidity measures of individual stocks on the NYSE and AMEX, while the innovation measure, PS_{INNOV}, captures serially uncorrelated innovations in the level measure. For both *PS* measures, we expect negative correlations with our risk aversion and uncertainty series. The fourth indicator is a measure of illiquidity proposed by Amihud (2002), *ILLIQ*. It is based on the daily ratios of absolute stock returns to their dollar volumes across NYSE stocks, averaged over a month. We expect positive correlations with our measures.

As Table 10 shows, the correlations with both uncertainty and risk aversion have mostly the expected sign and are statistically significant. The liquidity measure based on bond data, BLF_{FG}, is relatively more strongly correlated with our uncertainty measures, with correlations of 0.35 (for US uncertainty) and 0.45 (for German uncertainty). Liquidity measures based on NYSE and AMEX stocks, PS_{LEVEL} and PS_{INNOV}, show the strongest correlations with the US risk aversion series (0.34 and 0.28, respectively) but they also correlate with the German risk aversion and uncertainty series. The illiquidity measure based on Amihud (2002) shows high and statistically significantly positive correlations with the US risk aversion and uncertainty series, as well as the German uncertainty series.

In sum, bond market liquidity seems to correlate more strongly with uncertainty rather than risk aversion, while liquidity measures based on stocks correlated with both risk aversion and uncertainty.

Table 10
Risk aversion, uncertainty and liquidity.

	RA_t^{US}	RA_t^{GE}	UC_t^{US}	UC_t^{GE}
BLF_{FG}	−0.1564	−0.0884	−0.3515	−0.4526
	(0.0290)	(0.2190)	(<0.0001)	(<0.0001)
PS_{LEVEL}	−0.3400	−0.2294	−0.1879	−0.2675
	(<0.0001)	(0.0013)	(0.0085)	(0.0002)
PS_{INNOV}	−0.2773	−0.1620	−0.1099	−0.2107
	(0.0001)	(0.0236)	(0.1263)	(0.0031)
ILLIQ	0.3570	−0.0533	0.3614	0.5437
	(<0.0001)	(0.4596)	(0.0085)	(<0.0001)

Note: Correlations between the risk aversion and uncertainty measures for the US (superscript *US*) and Germany (superscript *GE*) and liquidity measures (*p*-values in parentheses): bond liquidity factor based on Fontaine and Garcia (2012) (BLF_{FG}); stock market liquidity measures based on Pastor and Stambaugh (2003) for liquidity levels (PS_{LEVEL}) and innovations in liquidity (PS_{INNOV}); stock market illiquidity based on Amihud (2002) (*ILLIQ*).

6. Conclusion

We propose a new method of extracting time-varying risk aversion from equity prices which is inspired by the dynamic asset pricing literature. We measure risk aversion and economic uncertainty by combining information in option-implied volatilities of stock prices, credit spreads, realized volatilities, interest rates, and survey-based measures of macroeconomic uncertainty. We apply this methodology to monthly data from both the US and Germany.

We then link our risk aversion and uncertainty measures to a large variety of risk aversion, stress and sentiment indices. Our resuls can be summarized as follows. First, we find our risk aversion measures to be significantly correlated with practitioner's measures of risk aversion (see Coudert and Gex, 2008 for a survey) but not with the low frequency economic measure of risk aversion as put forward in Campbell and Cochrane (1999). Sentiment indices, both as derived from financial data as in Baker and Wurgler (2006, 2007) or from consumer sentiment indices (as in Lemmon and Portnaiguina, 2006; Qiu and Welch, 2006) do not correlate highly with risk aversion. Second, these sentiment indexes also do not show strong and consistent correlations with our macro-economic uncertainty measures. However, stock market uncertainty and macro-economic uncertainty measure derived from a large number of conditional volatilities of macroeconomic series (Jurado et al., 2015) are highly correlated with our uncertainty measures. Third, the measures we derive are typically countercyclical but this effect is perhaps less strong and consistent than we expected. Fourth, both measures are robustly and strongly correlated with several popular financial stress indices and also with recently developed measures of flights-to-quality. Fifth, dispersion regarding forecasts of inflation and GDP also correlates highly with both our economic uncertainty and risk aversion measures. Finally, we find that bond liquidity seems to correlate more strongly with uncertainty rather than risk aversion while liquidity measures based on stocks are correlated with both risk aversion and uncertainty.

Our analysis also uncovers strong correlations between the risk aversion and uncertainty estimates for one country and various financial indices from the other country. This suggests that there is a global component in these series, and is consistent with the recent work in international finance (see Rey, 2015). Rey (2015) documents the existence of a global financial cycle, which is closely related to the VIX: low values of the VIX are associated with more capital inflows and outflows, more credit creation, more leverage and higher asset price inflation. She argues that the global financial cycle has profound implications for the conduct of monetary policy. It seems therefore important to further explore what drives the global financial cycle and how its drivers relate to time-varying risk aversion and uncertainty. This is left for future research.

Appendix A. The VIX and risk aversion

To obtain intuition on how the VIX is related to the actual ("physical") expected variance of stock returns and to risk preferences, we analyze a one-period discrete state economy. Imagine a stock return distribution with three different states x_i, as follows:

- Good state: $x_g = \mu + a$ with probability $(1-p)/2$,
- Bad state: $x_b = \mu - a$ with probability $(1-p)/2$,
- Crash state: $x_c = c$ with probability p,

where $\mu > 0,\ a > 0$ and $p > 0$ are parameters to be determined. We set them to match moments of US stock returns—the mean, the variance (standard deviation) and the skewness—while fixing the crash return at an empirically plausible number. The mean is given by:

$$\overline{X} = \frac{1-p}{2}x_g + \frac{1-p}{2}x_b + px_c = (1-p)\mu + pc. \tag{9}$$

The variance is given by:

$$V \equiv \sigma^2 = \frac{1-p}{2}(\mu + a - \overline{X})^2 + \frac{1-p}{2}(\mu - a - \overline{X})^2 + p(c - \overline{X})^2 \tag{10}$$

and the skewness (Sk) by:

$$V^{\frac{3}{2}}Sk = \frac{1-p}{2}(\mu + a - \overline{X})^3 + \frac{1-p}{2}(\mu - a - \overline{X})^3 + p(c - \overline{X})^3. \tag{11}$$

Consider an investor with power utility over wealth in a one-period world, so that in equilibrium she invests her entire wealth in the stock market:

$$U(\widetilde{W}) = E\left[\frac{(W_0\widetilde{R})^{1-\gamma}}{1-\gamma}\right], \tag{12}$$

where $\widetilde{R}$ is the gross return on the stock market, W_0 is initial wealth and γ is the coefficient of relative risk aversion.

The "pricing kernel" in this economy is given by marginal utility, denoted by m, and is proportional to $\widetilde{R}^{-\gamma}$. Hence, the stochastic part of the pricing kernel moves inversely with the return on the stock market. When the stock market is down, marginal utility is relatively high and vice versa.

The physical variance of the stock market is exogenous in this economy, and is simply given by V. This variance is computed using the actual probabilities. The VIX represents the "risk-neutral" conditional variance. It is computed using the so-called "risk-neutral probabilities," which are simply probabilities adjusted for risk. In particular, for a general state probability π_i for state i, the risk-neutral probability is:

$$\pi_i^{RN} = \pi_i \frac{m_i}{E[m]} = \pi_i \frac{R_i^{-\gamma}}{E[m]}. \tag{13}$$

So, for a given γ, we can easily compute the risk-neutral probabilities since $R_i = x_i + 1$. For an economy with three states, the risk-neutral variance is then given by:

$$VIX^2 = \sum_{i=1}^{3} \pi_i^{RN}(x_i - \overline{X}^{RN})^2, \tag{14}$$

where $\overline{X}^{RN} = \sum_{i=1}^{3}\pi_i^{RN}x_i$ is the risk-neutral mean. The variance premium is:

$$VP = VIX^2 - V = \sum_{i=1}^{3}\pi_i^{RN}(x_i - \overline{X}^{RN})^2 - \sum_{i=1}^{3}\pi_i(x_i - \overline{X})^2, \tag{15}$$

where $\pi_g^{RN} = \frac{1-p}{2}\frac{(\mu+a+1)^{-\gamma}}{E[m]}$, $\pi_b^{RN} = \frac{1-p}{2}\frac{(\mu-a+1)^{-\gamma}}{E[m]}$ and $\pi_c^{RN} = p\frac{(c+1)^{-\gamma}}{E[m]}$.

In our economy, the risk-neutral probability puts more weight on the crash state and the crash state induces plenty of additional variance, rendering the variance premium positive. The higher is risk aversion, the more weight the crash state gets, and the higher the variance premium will be.

A.1. Numerical examples

Suppose the statistics to match are as follows: $\overline{X} = 10\%,\ \sigma = 15\%$, both on an annualized basis; and $Sk = -1$ on a monthly basis. These numbers roughly match statistics for the aggregate U.S. stock market. We set $c = -25\%$ (a monthly number). This crash return is in line with the stock market collapses in October 1987 and October 2008. The implied crash probability

Table A1
The VIX and variance premium.

ParametersVIX		VIX	VP
Panel A: Varying γ, $Sk = -1$, $p = 0.5\%$			
$Sk = -1$, $\gamma = 2$		15.925	0.003
$Sk = -1$, $\gamma = 4$		17.342	0.008
$Sk = -1$, $\gamma = 6$		19.472	0.015
Panel B: Varying γ, $Sk = -2$, $p = 1\%$			
Parameters		VIX	VP
$Sk = -2$, $\gamma = 2$		16.838	0.006
$Sk = -2$, $\gamma = 4$		19.516	0.016
$Sk = -2$, $\gamma = 6$		23.194	0.031
Panel C: Varying W_{bm}, $\gamma = 4$, $Sk = -1$, $p = 0.5\%$			
Parameters	RRA	VIX	VP
$\gamma = 4$, $W_{bm} = 0$	4.000	17.342	0.008
$\gamma = 4$, $W_{bm} = 0.25$	5.323	19.059	0.014
$\gamma = 4$, $W_{bm} = 0.50$	7.968	26.010	0.045

Notes: Values of the VIX on an annualized basis in percent (VIX) and the annualized variance premium (VP) for different values of the underlying parameters, while keeping the crash return c fixed at -25%. In Panel A, the varying parameter is the coefficient of relative risk aversion γ while skewness Sk is fixed at -1. In Panel B, skewness Sk is fixed at -2. Panel C computes, for γ fixed at 4 and Sk fixed at -1, expected relative risk aversion (RRA) and the other four variables for different values of the benchmark wealth level W_{bm}.

to match the skewness coefficient of -1 is given by $p = 0.5\%$. With a monthly investment horizon, the crash probability implies a crash every 200 months, or roughly once every 15 years. Panel A of Table A1 provides, for different values of the coefficient of relative risk aversion γ, the values for the VIX on an annualized basis in percent (*VIX*) and the annualized variance premium (*VP*). Note that the variance premium is monotonically increasing in the coefficient of relative risk aversion γ.

In structural models, γ is typically assumed to be time-invariant, and the time variation in the variance premium is generated through different mechanisms. For example, in Drechsler and Yaron (2011), who formulate a consumption-based asset pricing model with recursive preferences, the variance premium is directly linked to the probability of a "negative jump" to expected consumption growth. The analogous mechanism in our simple economy would be to decrease the skewness of the return distribution by increasing the crash probability p. This obviously represents "risk" instead of "risk aversion". Yet, it is the interaction of risk aversion and skewness that gives rise to large readings in our risk aversion proxy. To illustrate, let us consider an example with lower skewness. Setting skewness equal to -2 requires a higher crash probability of $p = 1\%$. Panel B of Table A1 shows that the VIX increases, and increases more the higher the coefficient of relative risk aversion, both in absolute and in relative terms. The variance premium roughly doubles for all γ levels.

In Bekaert et al. (2010), when a recession becomes more likely, the representative agent also becomes more risk averse through a Campbell–Cochrane (1999)-like external habit formulation. The recession fear then induces high levels of the VIX. We can informally illustrate such a mechanism in our one-period model. Imagine that the utility function is over wealth relative to an exogenous benchmark wealth level W_{bm}. Normalizing the initial wealth W_0 to 1, the pricing kernel is now given by $(\widetilde{R} - W_{bm})^{-\gamma}$, and the coefficient of relative risk aversion is $\gamma\widetilde{R}/(\widetilde{R} - W_{bm})$. Consequently, risk aversion is state dependent and increases as $\widetilde{R}$ decreases towards the benchmark level. It is easy to see how a dynamic version of this economy, for instance with a slow-moving W_{bm}, could generate risk aversion that is changing over time as return realizations change the distance between actual wealth and the benchmark wealth level.

To illustrate this mechanism, Panel C considers three different benchmark levels for W_{bm} (0.05, 0.25 and 0.5) with γ fixed at 4 and $Sk = -1$, implying $p = 0.5\%$. The second column shows expected relative risk aversion in the economy (RRA), weighting the three possible realizations for risk aversion with the actual state probabilities. The other columns are as in the panels above. Clearly, for $W_{bm} = 0$, RRA = 4 and we replicate the values in Panel A for $\gamma = 4$. Keeping γ fixed and increasing W_{bm}, effective risk aversion increases. For example, RRA increases from 5.323 to 7.968 as W_{bm} increases from 0.25 to 0.5. The VIX increases from 19.059 to 26.010 and the variance premium more than triples from 0.014 to 0.045.

Appendix B. Quantifying qualitative data

A widely used method for quantifying survey data is the so-called Probability Approach of Carlson and Parkin (1975).[5] Their method assumes that respondents have a common subjective probability distribution over the future development of a variable and that they report a variable to go up or down if the median of their subjective probability distribution lies above or below an indifference interval.

Respondent i bases his qualitative answer on a subjective probability distribution over the possible values of the variable in question. These subjective probability distributions are statistically independent and normally distributed with finite mean and variance. The respondents are supposed to report the mean of the distribution. An individual respondent states in his response whether the variable in question will worsen/decrease ($DOWN_{i,t}$); improve/increase ($UP_{i,t}$) or remain unchanged ($SAME_{i,t}$).

The individual answer is $DOWN_{i,t}$, if the mean of the expected value of the change in the variable x by the end of time $t+k$, $E[\Delta x_{i,t+k}]$, is smaller than $a_{i,t}$ (an upper indifference bound):

$$E[\Delta x_{i,t+k}] < a_{i,t}.$$

Similarly, the individual answer is $UP_{i,t}$, if $E[\Delta x_{i,t+k}]$ is larger than $b_{i,t}$ (a lower indifference bound):

$$E[\Delta x_{i,t+k}] > b_{i,t}.$$

Finally, the individual answer is $SAME_{i,t}$, if $E[\Delta x_{i,t+k}]$ is between the lower and upper boundary of the indifference interval $a_{i,t}$ and $b_{i,t}$:

$$b_{i,t} \leqslant E[\Delta x_{i,t+k}] \leqslant a_{i,t}.$$

Further assumptions of the Probability Approach:

(1) Making use of the Central Limit Theorem, the aggregate distribution of the basic population can be approximated by a normal distribution.[6]

(2) The upper and lower indifference bounds are identical for all respondents in the population:

$$a_{i,t} = a_t \text{ and } b_{i,t} = b_t.$$

These assumptions allow us to interpret survey results as an independent drawing from the aggregate distribution of expectations with mean $E[\Delta x_{t+k}]$ and standard deviation σ_{t+k}. Hence, the percentages of the responses expecting a rise and a fall, denoted by UP_t and $DOWN_t$, converge to the corresponding population values:

$$1 - UP_t = \Phi\left(\frac{b_t - E\Delta x_{t+k}}{\sigma_{t+k}}\right)$$

and

[5] The probability approach was first employed by Theil (1952) and was rediscovered by Carlson and Parkin (1975) who used the method to construct quantitative measures for inflation expectations.

[6] Other distributions have been suggested in the literature, e.g. t-distribution. In our sample, using t-distribution yields very similar results.

$$DOWN_t = \Phi\left(\frac{a_t - E[\Delta x_{t+k}]}{\sigma_{t+k}}\right),$$

where Φ is the cumulative distribution function of a standard normal. The quantiles are given by:

$r_t = \Phi^{-1}(1 - UP_t)$ and $f_t = \Phi^{-1}(DOWN_t)$.

(3) Indifference bounds are symmetric and time-invariant: $-a_t = b_t = c$.

Solving for $E[\Delta x_{t+k}]$ and σ_{t+k} yields

$$E[\Delta x_{t+k}] = \frac{b_t f_t + a_t r_t}{f_t - r_t} = c\frac{f_t + r_t}{f_t - r_t}$$

and

$$\sigma_{t+k} = -2c\frac{1}{f_t - r_t}.$$

(4) Determining c: Since we are only interested in the time series of the standard deviation, all the relevant information is contained in r_t and f_t variables (quantiles). We choose c to scale $\frac{-2}{f_t - r_t}$ such that the resulting time series is of an order of magnitude corresponding to the Survey of Professional Forecasters data.[7]

Appendix C. Description of indicators

In this Appendix, we present a description of the various indicators used. Indicators are listed alphabetically by their abbreviation.

BC (forecast dispersion based on the US Blue Chip Economic Indicator forecast data for the CPI and real GDP): the cross sectional standard deviation of the forecasts of CPI and real GDP.

BLF_{FG} (bond liquidity factor based on Fontaine and Garcia, 2012): this latent liquidity premium is measured by estimating a term structure model from a panel of pairs of U.S. Treasury securities, where each pair has similar cash flows but different ages. In crisis periods, this liquidity measure is low.

BOS ("balance" indicator based on the US Business Outlook survey for future, *F*, and current, *C*, business conditions): the Manufacturing Business Outlook Survey is a monthly survey of manufacturers in the Third Federal Reserve District. Participants indicate the direction of change (decrease, no change, increase) in overall business activity for the next month (current activity) and six months from now (future activity). "Balance" indicator is the difference between proportions of optimistic versus pessimistic respondents so that high values of the index indicates a higher proportion of optimistic respondents.

CCI (OECD consumer confidence indicators): based on households' plans for major purchases and their economic situation, both currently and their expectations for the immediate future. Opinions compared to a "normal" state are collected and the difference between positive and negative answers provides a qualitative index on economic conditions. High values of the indicators correspond to a higher proportion of positive answers.

CFNAI (the Chicago Fed National Activity Index): a zero value for the index indicates that the US economy is expanding at its historical trend rate of growth; negative values indicate below-average growth; and positive values indicate above-average growth.

CISS (the Composite Index of Systemic Stress based on the US and European Monetary Union, EMU, data): combines information from the money, equity, bond, and foreign exchange markets, and some financial intermediaries-related information. The indicators mostly comprise realized volatilities for various return, currency and interest rate measures.

CV_{BH} (conditional stock market variance measure based on Bekaert and Hoerova, 2014): estimate of the expected stock market variance based on the projection of future realized monthly variances onto current daily, weekly, monthly realized variances and the option-implied variance (for Germany, we omit the option-implied variance in the projection).

CV_{BTZ} (conditional stock market variance measure based on Bollerslev et al., 2009): estimate of the expected stock market variance based on the martingale model.

CV_{CFNAI} (conditional variance of the Chicago Fed National Activity Index): conditional variance of the Chicago Fed National Activity Index (CFNAI) estimated using a GARCH(1,1) model.

CV_{IP} (conditional variance of the industrial production): conditional variance of the US industrial production index estimated using a GARCH(1,1) model.

FTS (flight-to-safety measure based on Baele et al., 2013): using daily bond and stock return data, *FTS* is a {0,1} dummy variable that identifies whether on a particular day a FTS took place. Flight-to-safety is characterized by market stress (high equity and perhaps bond return volatility), simultaneous high bond and low equity returns, and a low (negative) correlation between bond and equity returns. Daily *FTS* dummies are transformed to a monthly indicator by taking the proportion of *FTS* days within a month.

FTQ (flight-to-quality measures based on Mueller et al., 2012): the difference between implied volatility of the US stock market, the VIX index, and the implied volatility of the US Treasuries market, TIV. TIV is constructed in a similar manner as the VIX index. It is a square root of the one month implied variance for futures on 30 year Treasuries. The implied variance is constructed within model-free method as proposed by Britten-Jones and Neuberger (2000).

GFK (German Gfk consumer sentiment indicator for business cycle, *BC*, income, *IN*, and willingness to spend, *WS*): based on a monthly survey of about 2000 consumers, asking them about (1) their expectations about the business cycle; (2) their income and (3) their willingness to spend. High values of the index indicate that consumers are optimistic.

IFO ("balance" indicator based on the German Ifo Business Climate survey for business climate, *BC*, business situation, *BS*, and business expectations, *BE*): based on a survey of German manufacturing firms. The "Business Climate" combines two sub-indicators, "Business Situation" (referring to the current business climate) and "Business Expectations" (referring to the future climate). "Balance" indicator is the difference between proportions of optimistic versus pessimistic respondents so that high values of the index indicates a higher proportion of optimistic respondents.

ILLIQ (stock market illiquidity based on Amihud, 2002): the average across stocks (NYSE stocks over 1967–2010) of daily ratio of absolute stock return to its dollar volume, subsequently averaged over a month. High values of the index indicate high illiquidity.

IMF (the IMF Financial Stress Index): a weighted sum of 7 components, "banking-sector beta", TED spread, inverted term spread, stock market returns, time-varying stock market volatility, sovereign debt spread, and exchange market volatility (see Balakrishnan et al., 2009, for details).

Kansas (the Kansas City Financial Stability Index): combines a large number of interest rate variables such as the TED spread and the off/on-the-run-Treasury spread; a number of corporate yield spreads, risk indicators drawn from banking stock returns, but also the stock–bond return correlation and the VIX itself (see Hakkio and Keeton, 2009, for details).

[7] We thank M.H. Pesaran for a very helpful discussion of issues surrounding quantification of qualitative expectations. For a survey, see Nardo (2003) and Pesaran and Weale (2005).

MCSI (US Michigan consumer sentiment indicator): a survey of consumer attitudes concerning both the present situation as well as expectations regarding economic conditions is conducted by the University of Michigan. High values of the index indicate that consumers are optimistic.

MUC_{JLN} (macroeconomic uncertainty measures based on Jurado et al., 2015): a weighted sum of the conditional volatilities of the purely unforecastable component of the future value of 132 global financial and macroeconomic series, measured within one, three and twelve month's windows. That is, the macroeconomic uncertainty, *MUC*, for each variable, *y*, within a time-window of length *h* is given by: $MUC^y_{jt}(h) = \sqrt{E\left[\left(y_{j\ t+h} - E\left[y_{j\ t+h|I_t}\right]\right)^2 |I_t\right]}$. Note that only 25 out of 132 series are financial (the authors argue that in order to obtain a broad-based measure of uncertainty, it is desirable not to over–represent the financial series, which tend to be far more volatile than the macro series).

NFCI (the Chicago Fed National Financial Conditions Index): positive values of the NFCI indicate financial conditions that are tighter than average, while negative values indicate financial conditions that are looser than average.

PS (stock market liquidity measures based on Pastor and Stambaugh (2003) for liquidity levels, *LEVEL*, and innovations, *INNOV*): the *LEVEL* liquidity measure is the equally weighted average of the liquidity measures of individual stocks on the NYSE and AMEX. The liquidity measure for stock *i* in month *t* is the ordinary-least-square estimate of $c_{i,t}$ in the following regression: $r^e_{i,d+1,t} = a_{i,t} + b_{i,t}r_{i,d,t} + c_{i,t}sign(r^e_{i,d,t})v_{i,d,t} + e_{i,d+1,t}$ where $r_{i,d,t}$ is the return on stock *i* on day *d* in month $t, r^e_{i,d,t} = r_{i,d,t} - r_{m,d,t}$ where $r_{m,d,t}$ is the return on the CRSP value-weighted market return on day *d* in month *t*; and $v_{i,d,t}$ is the dollar volume for stock *i* on day *d* in month *t*. We expect $c_{i,t}$ to be negative in general and larger in absolute magnitude when liquidity is lower. The basic idea is the we expect that the volume signed by the contemporaneous return on the stock in excess of the market should be accompanied by a return that one expects to be partially reversed in the future if the stock is not perfectly liquid (large volume trades on day *d* are followed by lower returns on day $d+1$). The *INNOV* measure is constructed by first regressing the scaled monthly difference on its lags as well as the lagged values of the scaled level series, and then taking the fitted residuals divided by 100.

PUC_{BBD} (policy uncertainty index based on Baker et al., 2013): index constructed from three types of underlying components, a component that quantifies newspaper coverage of policy-related economic uncertainty, a component that reflects the number of federal tax code provisions set to expire in future years, and a component based on disagreement among economic forecasters as a proxy for uncertainty (using the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters). The German index, constructed similarly, starts in January 1997.

RA_{CC} (Campbell and Cochrane, 1999): local relative risk aversion based on the Campbell and Cochrane (1999) model of external habit and obtained from Bekaert and Engstrom (2010). Risk aversion is a function of the "surplus consumption" ratio, which measures deviations of the real nondurable consumption from the "habit stock," a moving average of past consumption levels.

RAI (Credit Suisse First Boston Risk Appetite Index): the value of the index on a given day is the slope coefficient obtained from the cross-sectional linear regression of risk and excess returns. The more positive the index, the greater is the risk appetite. The index is based on daily data for 64 indexes of bonds and equities in developed and emerging markets. Daily indexes of local currencies are used for developed markets, while daily U.S.-dollar indexes are used for emerging markets.

RTI (JP Morgan G10 Risk Tolerance Index): composed of four components: (1) US swap spread (to capture liquidity risk); (2) VIX (to capture equity market risk); (3) EMBI+ (to capture credit risk in emerging markets); and (4) trade-weighted Swiss franc (to capture risk attitude in currency markets). The index is constructed as an equally weighted average after having standardized the four components. High values of the index indicate high risk aversion.

$Sent_{BW}$ (sentiment indicator based on Baker and Wurgler, 2007): the first principal component of six sentiment proxies (trading volume as measured by NYSE turnover; the dividend premium; the closed-end fund discount; the number and first-day returns on IPOs; and the equity share in new issues) over 1962–2011. High values of the index imply that investors are optimistic. Definition of sentiment from Baker and Wurgler: "Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand".

SPF (forecast dispersion for the US Survey of Professional Forecasters): the cross sectional standard deviation of the forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.

VP_{BH} (variance premium measures based on Bekaert and Hoerova, 2014): the difference between the implied stock market variance and conditional stock market variance CV_{BH} defined above.

VP_{BTZ} (variance premium measures based on Bollerslev et al., 2009): the difference between the implied stock market variance and conditional stock market variance CV_{BTZ} defined above.

References

Allen, L., Bali, T., Tang, Y., 2012. Does systemic risk in the financial sector predict future economic downturns? Review of Financial Studies 25, 3000–3036.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Anderson, E., Ghysels, E., Juergens, J., 2009. The impact of risk and uncertainty on expected returns. Journal of Financial Economics 94, 233–263.

Baele, L., Bekaert, G., Inghelbrecht, K., Wei, M., 2013. Flights to Safety. NBER Working paper no 15260.

Baker, S.R., Bloom, N., Davis, S.J., 2013. Measuring Economic Policy Uncertainty. Working paper.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645–1680.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. Journal of Economic Perspectives 21, 129–151.

Balakrishnan, R., Danninger, S., Elekdag, S., Tytell, I., 2009. The Transmission of Financial Stress from Advanced to Emerging Economies. IMF Working Paper WP/09/133.

Bali, T., Zhou, H., 2012. Risk, uncertainty, and expected returns. Journal of Financial and Quantitative Analysis, forthcoming.

Bali, T., Peng, L., Shen, Y., Tang, Y., 2014. Liquidity shocks and stock market reactions. Review of Financial Studies 27, 1434–1485.

Bali, T., Brown, S.J., Tang, Y., 2015. Macroeconomic Uncertainty and Expected Stock Returns. Working paper.

Bansal, R., Yaron, A., 2004. Risks for the long run: a potential resolution of asset pricing puzzles. Journal of Finance 59, 1481–1509.

Bansal, R., Khatchatrian, V., Yaron, A., 2005. Interpretable asset markets? European Economic Review 49, 531–560.

Beber, A., Brandt, M., 2009. Resolving macroeconomic uncertainty in stock and bond markets. Review of Finance 13, 1–45.

Bekaert, G., Engstrom, E., 2010. Inflation and the stock market: understanding the fed model. Journal of Monetary Economics 57, 278–294.

Bekaert, G., Engstrom, E., Grenadier, S., 2010. Stock and bond returns with moody investors. Journal of Empirical Finance 17, 867–894.

Bekaert, G., Engstrom, E., Xing, Y., 2009a. Risk, uncertainty, and asset prices. Journal of Financial Economics 91, 59–82.

Bekaert, G., Hoerova, M., 2014. The VIX, the variance premium and stock market volatility. Journal of Econometrics 183, 181–192.

Bekaert, G., Hoerova, M., Lo Duca, M., 2013. Risk, uncertainty, and monetary policy. Journal of Monetary Economics 60, 771–788.

Bekaert, G., Hoerova, M., Scheicher, M., 2009b. What do asset prices have to say about risk appetite and uncertainty? ECB working paper no. 1037.

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77, 623–685.

Bollerslev, T., Gibson, M., Zhou, H., 2011. Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. Journal of Econometrics 160, 235–245.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Stock returns and variance risk premia. Review of Financial Studies 22, 4463–4492.
Brandt, M., Wang, K.Q., 2003. Time-varying risk aversion and unexpected inflation. Journal of Monetary Economics 50, 1457–1498.
Britten-Jones, M., Neuberger, A., 2000. Option prices, implied price processes, and stochastic volatility. Journal of Finance 55, 839–866.
Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: a consumption based explanation of aggregate stock market behavior. Journal of Political Economy 107, 205–251.
Canova, F., Marrinan, J., 1998. Sources and propagation of international output cycles: common shocks or transmission? Journal of International Economics 46, 133–166.
Carlson, J.A., Parkin, M., 1975. Inflation expectations. Economica 42, 123–138.
Carr, P., Wu, L., 2009. Variance risk premiums. Review of Financial Studies 22, 1311–1341.
Chicago Board Options Exchange, 2004. VIX CBOE Volatility Index. White paper.
Corsi, F., 2009. A simple approximate long memory model of realized volatility. Journal of Financial Econometrics 7, 174–196.
Coudert, V., Gex, M., 2008. Does risk aversion drive financial crises? testing the predictive power of empirical indicators. Journal of Empirical Finance 15, 167–184.
Diether, K.B., Malloy, C.J., Scherbina, A., 2002. Differences of opinion and the cross section of stock returns. Journal of Finance 57, 2113–2141.
Drechsler, I., Yaron, A., 2011. What's vol got to do with it. Review of Financial Studies 24, 1–45.
Duan, J.-C., Yeh, C., 2010. Jump and volatility risk premiums implied by VIX. Journal of Economic Dynamics and Control, Elsevier 34 (11), 2232–2244, November.
Eickmeier, S., 2007. Business cycle transmission from the us to Germany – a structural factor approach. European Economic Review 51, 521–551.
Fama, E.F., Schwert, G.W., 1979. Inflation, interest, and relative prices. Journal of Business 52, 183–209.
Fontaine, J.-S., Garcia, R., 2012. Bond liquidity premia. Review of Financial Studies 25, 1207–1254.
Gai, P., Vause, N., 2006. Measuring investors' risk appetite. International Journal of Central Banking 2, 167–188.
Gordon, S., St-Amour, P., 2004. Asset returns with state-dependent risk preferences. Journal of Business and Economic Statistics 22, 241–252.
Hakkio, C.S., Keeton, W.R., 2009. Financial stress: what is it, how can it be measured, and why does it matter? Economic Review, Federal Reserve Bank of Kansas City, issue Q II, 5–50.
Hamilton, J.D., 1985. Uncovering market expectations of inflation. Journal of Political Economy 93, 1224–1241.
Heber, G., Lunde, A., Shephard, N., Sheppard, K., 2009. Oxford-Man Institute's Realized Library. Oxford-Man Institute, University of Oxford.
Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. American Economic Review 105, 1177–1216.
Holló, D., Kremer, M., Lo Duca, M., 2012. CISS – a composite indicator of systemic stress in the financial system. Working paper series 1426, European Central Bank.
Lemmon, M., Portnaiguina, E., 2006. Consumer confidence and asset prices: some empirical evidence. Review of Financial Studies 19, 1499–1529.
Menzly, L., Santos, T., Veronesi, P., 2004. Understanding predictability. Journal of Political Economy 112, 1–47.
Mueller, P., Vedolin, A., Yen, Y., 2012. Bond variance risk premia. FMG discussion papers DP699, Financial Markets Group.
Nardo, M., 2003. The quantification of qualitative survey data: a critical assessment. Journal of Economic Surveys 17, 645–668.
Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.
Pastor, L., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of Financial Economics 110, 520–554.
Pesaran, M.H., Weale, M., 2005. Survey expectations. In: Elliott, G., Granger, C.W.J., Timmermann, A. (Eds.), Handbook of Economic Forecasting. North-Holland.
Qiu, L., Welch, I., 2006. Investor sentiment measures. Working paper, Brown University.
Rajan, R., 2006. Has finance made the world riskier? European Financial Management 12, 499–533.
Rey, H., 2015. Dilemma not trilemma: the global financial cycle and monetary policy independence. NBER working paper no. 21162.
Sharpe, W.F., 1990. Investor wealth measures and expected return. Quantifying the Market Risk Premium Phenomenon for Investment Decision Making, The Institute of Chartered Financial Analysts, 29–37.
Stock, J.H., Watson, M.W., 2012. Disentangling the channels of the 2007–2009 recession. Brookings Papers on Economic Activity, Spring 2012, pp. 81-135.
Theil, H., 1952. On the Shape of economic microvariables and the munich business test. Révue de l'Institut International de Statistique 20, 105–120.
Wachter, J., 2006. A consumption-based model of the term structure of interest rates. Journal of Financial Economics 79, 365–399.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48, 817–838.