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**Uncertainty Shocks and the Term Structure of Interest Rate: a
Cross-Country Comparison with Dynamic Latent Factor Approach**

**Bizonytalansági sokkok és a hozamgörbe: országok közötti összehasonlítás
dinamikus látens faktor modellek segítségével**

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Abstract. How does the yield curve respond to shocks of financial and macroeconomic uncertainty? I investigate this question by estimating vector-autoregressive models (VAR) on US, Germany, Japan and UK zero-coupon yield data. The smooth curves are obtained with the parsimonious method of Diebold and Li [2006], where the factors represent the level, slope and curvature. The jumps of both macroeconomic and financial uncertainty - as measured by Jurado et al. [2015] and Jurado et al. [2019] – are associated with a negative and significant response of the entire yield spectrum, but the short-end is found to be more responsive. Rolling-window analysis showed that this curve steepening phenomenon exhibits substantial dynamic variations, which can partly be a consequence of the zero lower bound monetary policy. Incorporating inflation and industrial production revealed that macroeconomic fundamentals account for a large share of yield variations following uncertainty jumps. My findings are consistent with various interpretations, such as with those emphasizing investor's expectations, monetary actions or decreased labor demand in uncertain times. My results remain robust to various data treatments, however, the exogeneity assumption on uncertainty is found to bear large empirical importance.

keywords: uncertainty shocks, yield curve, latent factors, vector-autoregression, Nelson-Siegel, inflation, industrial production

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1 Introduction

Since the influential paper by Bloom [2009], there has been a growing amount of literature focusing on the effects of uncertainty shocks. The increased policy and research attention towards uncertainty is mainly a consequence of the Great Recession, under which uncertainty *by itself* is proven to have played a vast role. Moreover, the flourishing number of empirical proxies, such as surveys or news databases, facilitated the creation of myriads of uncertainty indicators. The general aim is to measure the extent of unforeseeability surrounding the economy, which can originate from many sources. The uncertainty in financial or real economic movements, economic, monetary or trade policy changes, geopolitical events and variations in individual attitudes (such as risk aversion) are some of the most important sources (Jurado et al. [2015], Jurado et al. [2019], Baker et al. [2016], Husted et al. [2020], Caldara and Iacoviello [2018], Bekaert et al. [2021]).

Although, many of these indices stand on different conceptual and methodological grounds, they can typically be characterized by including both the Knightian sense of uncertainty and measurable risk (Bloom [2014]). Furthermore, other common attributes are frequently highlighted (Bloom [2014]; Castelnuovo et al. [2017]). They (1) exhibit a strong co-movement with real economic activity indicators; (2) behave countercyclically, so they rise rapidly under recessions and fall in booms. This close connection between uncertainty and the business cycle naturally raises the question of causal directions in uncertainty research. Solving this problem is still an open challenge for empirical investigations, and a solid theoretical ground is needed.

The role of uncertainty in macroeconomics is examined under various contexts. Its relations with financial frictions, capital flows or policy effectiveness are some important areas of investigation (see e.g. Castelnuovo et al. [2017], Gilchrist et al. [2014], Caldara et al. [2016], Shang [2022]). However, relatively fewer studies exist with the focus on the direct impacts of uncertainty on the term structure of interest rates. As the yield curve essentially captures the investors' expectations on future returns and represents the financing costs of investments, it is of paramount importance to better understand its driving forces. Moreover, since the central banks primarily exert effect on the economy via interest rate setting, such results naturally bear important monetary policy implications. The straightforward practice to investigate such uncertainty-yield interactions is to regress yields of various maturities on different uncertainty metrics. For example, a vector-autoregressive (VAR) model can be an obvious choice. However, besides this solution is not parsimonious, unrestricted VAR models are wasteful of degrees of freedom.

Fortunately, the yields are no exception to the appealing statistical and theoretical property shared by many economic and financial phenomena: that a few underlying factors give an accurate description of a seemingly difficult, high-dimensional problem. Statistically, it is shown

that the first three principal components explain well above 95 percent of the variation of bond yields (e.g. Diebold and Li [2006], Joslin et al. [2014]). Many proposed yield curve models utilize this property, but the suggested number of factors varies across scholars. There are single-factor models (e.g. the short-rate model of Vasicek [1977]) and more flexible solutions with three, four or more factors (Diebold and Li [2006], Nelson and Siegel [1987]; Svensson [1994]; Björk and Christensen [1999]) included. The latter are sometimes more useful for catching certain shape variations, for example curves with more than one humps/troughs. Besides the data being consistent with it, economic theory also supports factor structure. For example, the myriads of asset returns can be explained by their risk premium - driven by a small number of risk factors -, which is the basis of the capital-asset pricing model (CAPM), a single-factor model with remarkable explanatory power.

The main question of my research is the following: "*How does financial and macroeconomic uncertainty affect the yield curve*"? I try to examine this in four developed countries, by estimating vector-autoregressive (VAR) models. The proxy for financial uncertainty is proposed by Jurado et al. (2019), and the macro is due to Jurado et al. [2015]. For catching the dynamic evolution of the yield curve, I apply the parsimonious, three-factor modeling technique of Diebold and Li [2006].¹ The latent factors of the model can be interpreted as *level*, *slope* and *curvature*, and they are shown to perform well in forecasting future yields, in comparison with other methods (Diebold and Li [2006]). This solution is suitable for vector-autoregressive modeling, because the dynamic response of the *three* factors defines the behavior of the *entire* yield curves. Moreover, it is suspected that the first two factors are strongly related to macroeconomic variables (Diebold et al. [2006]). Namely, the level factor is highly correlated with inflation and the slope factor has a tight comovement with the cyclical behavior of the economy. Given these relationships, I extend my models with the above two macroeconomic fundamentals and attempt to explain my findings about the factor/yield curve reactions to uncertainty jumps.

My results show that heightened uncertainty contributes to yield drops at all maturities. The slope factor's response reveals that the yield curves get steeper, meaning that the short-end has a more intense negative response. These findings are in line with those of Castelnovo [2019]. Rolling window analysis points to weak evidence in favor of the role of monetary policy in managing risks. Under the windows when zero lower bound (ZLB) gets more weight, the spread reaction becomes negative. This connects my study to the paper of Caggiano et al. [2014], Basu and Bundick [2017], Aastveit et al. [2017], Shang [2022] and others who examine the combined effects of ZLB and uncertainty. Incorporating inflation and industrial production to my models lend support that the yield movements are also related to expectations. Both macro fundamental drops under elevated uncertainty, which categorizes its shocks as demand types, such as in Leduc and Liu [2016]. Variance decompositions reveal that a huge proportion

¹I refer to their model as Diebold-Li model, but technically, it belongs to Nelson and Siegel [1987] model family, which uses preparameterised curves for estimation. I will further explain this in the subsequent sections.

of yield movements after uncertainty shocks happen through macroeconomic fundamentals. The observed medium-term rebound in production is theoretically grounded by Bloom [2009], as a consequence of resource-reallocation from low to highly productive firms in uncertain times. It is also empirically detected by Caggiano et al. [2014] and Castelnuovo [2019] and can explain the more intense short-yield drops, as revealed by Castelnuovo [2019]. The drop of inflation lowers the yields but its effect on the curve rotation is not straightforward. Finally, my preliminary Granger-causality estimation results are weak evidence in favor of uncertainty being either an exogenous (Baker and Bloom [2013]), or a mixture of exogenous and endogenous source of the yield variations (Ludvigson et al. [2021]).

My paper is organized as follows. Section 2 describes some popular uncertainty proxies and reviews various empirical results and theories related to uncertainty and the macroeconomic environment. A brief discussion about the question of causal directions regarding uncertainty is also provided here. Section 3 describes the latent factor yield curve modeling technique and my empirical model. Section 4 presents my data and sample period. Section 5 provides my empirical results in the following way. Firstly, an evaluation of the Diebold-Li model fitting is given, followed by my findings regarding causal relations, which can aid correct model specification. Secondly, I present my main empirical results about uncertainty-yield relations and some evidence about their possible economic driving forces. Section 6 is a succinct description about the robustness of my findings to alternative data treatments and other model specifications. Section 7 concludes.

2 Literature review

2.1 Measuring uncertainty

Various methods can be found in the literature to create uncertainty proxies. Some of the quickly growing solutions are the text-based and model-based approaches.

The popular economic policy uncertainty index (EPU) by Baker et al. [2016] uses own-country newspaper articles and counts the number of keywords referring to policy uncertainty and create a GDP-weighted average of them. In a similar vein, Husted et al. [2020] construct a measure for monetary policy uncertainty. The same methodology is used by Caldara and Iacoviello [2018], who create an indicator which tries to catch the magnitude of geopolitical risk (GPR) by counting the number of times words related to geopolitical stress – such as war or terrorism - appear in prominent international newspapers. Some closely related, words- and text-based group of metrics are the twitter, google trend or web-search based indices (e.g. Castelnuovo and Tran [2017]; Bontempi et al. [2021]). Their attractive feature is the ability to

generate high frequency data, but some of their drawbacks are their partial unavailability before the 2010s, or their non-representativeness of the population. A different category of indicators uses surveys, for example by measuring the level of disagreement amongst professional forecasters (Survey of Professional Forecasters).

A widely-used financial uncertainty proxy is the equity-market's expected volatility index (VIX) constructed by the Chicago Board Options Exchange, based on S&P 500 index options (the 'fear index'). In my analysis, I choose the model-based financial and macroeconomic uncertainty indices by Jurado et al. (2019) and Jurado et al. [2015], which are proven to be powerful determinants of various economic phenomena (see e.g. Connolly et al. [2018], Castelnuevo [2019] amongst others).² These are *by-construction* incorporating the assumption that uncertainty refers to the unpredictability of the economy. Instead of making use of one specific proxy, they remove the forecastable components from almost 150 financial and/or real macro indicators, and create an aggregate index from the common variation of these individual series. The macro dataset uses the FRED monthly database (described in McCracken and Ng [2016]), the finance-only dataset's detailed description is provided in Ludvigson et al. [2017]. The individual indices cover a wide range of economic areas. They include proxies e.g. for industrial production, unemployment, housing market, bond returns and spreads, inflation and many other important measures, which are indicative to the condition of the economy. Both indices are created to 1, 3 and 12 months horizon, and their values are normalized. Following the common practice of the literature (e.g. Connolly et al. [2018]), I choose the quarter-year index.

2.2 Uncertainty and the macroeconomic environment

My study has a close connection with other strands of the literature.

An important direction in uncertainty research examines the combined effects of financial frictions and uncertainty (Castelnuevo et al. [2017]). Many evidence suggest that uncertainty jumps have more negative effects on the business cycle in times of high financial distress, because increased external financing costs make it riskier to insure against investing in inputs (Arellano et al. [2019]). Gilchrist et al. [2014] find that financial frictions amplify the effect of uncertainty shocks on investment. Capital liquidity drops together with the irreversibility of investments heightens the firms' "wait-and-see" behavior – the postponement of investment - under elevated uncertainty. The results of Alessandri and Mumtaz [2019] also support this channeling effects of financial frictions. They treat uncertainty in an endogenous way, proxied by the average volatility of the economy's structural shocks to rule out the agents' ability to forecast economic conditions, and capture the economy's financial condition with the Chicago Fed's Financial Condition Index. The estimated VAR models point to considerable differences

²Castelnuevo [2019] praises the financial index as a 'state-of-art'.

in the magnitude of the effects of uncertainty with financial regime switches.

In a close spirit, Caldara et al. [2016] conclude that elevated uncertainty – even when identified separately from financial asset price proxies - is especially harmful for the economy under tight financial conditions, and this combination was likely a prominent driver of the Great Recession. Generally, investment likely reacts more intensively to uncertainty changes due to the more forward-looking attitude of firms compared to that of households (Bloom [2017]). Cheng and Chiu [2018] show that geopolitical risk (à la Caldara and Iacoviello [2018]) is tightly connected to business cycle fluctuations in emerging countries. On a sample of 38 developing countries, the results of the structural VAR models indicate that GPR shocks explain 22 percent of the aggregate output, 15 percent of the trade balance, 19 percent of consumption and 11 percent of investment movements on average (the values highly vary across countries). Their results are mainly robust to various other uncertainty indices.

A great deal of literature investigates the relationship between monetary policy and uncertainty. Caggiano et al. [2017] show that the effects of uncertainty shocks are significantly more intensive under recessions than non-recessionary times and monetary policy is dampened in stabilizing real economic activities in the short run. A large number of real activity indicators is shown to drop when uncertainty occurs together with economic downturns (Caggiano et al. [2014]). Other investigations in that direction also show that uncertainty alters the effects of Fed measures on real macro variables such as output, investment or consumption (Aastveit et al. [2017]). A possible explanation to these is the so-called real option theory of uncertainty (Bernanke [1983]), which states that heightened uncertainty strengthens firms wait-and-see behavior and makes them less responsive to policy changes, which in turn amplifies the recessionary effects. Consumption drop is likely due to the increased precautionary savings of households. The combined effects of uncertainty and the zero lower bound (ZLB) is also scrutinized. The results indicate that uncertainty hits harder under ZLB periods (Basu and Bundick [2017]; Shang [2022]). The study of Tillmann [2020] examines how the term structure of interest rate reactions vary to monetary measures depending on the level of uncertainty. In high-uncertainty regimes, the positive jump of yields to monetary policy shocks is significantly lower, especially for longer-term maturities. The paper divides the yields into expectations and term premia components. It seems that the response of expectations component of the future short rates is not affected by the regime, but the term premia exhibit stronger negative response when uncertainty is higher. Consequently, it is likely the result of the latter component that makes monetary policy actions less effective on determining bond yields.

A common important practical implication of the results of the above discussed studies is that monetary policy should be as predictable as possible to be able to exert its intended effect. Connolly et al. [2018] identify macroeconomic uncertainty (by Jurado et al. [2015]) as a main driver of the persistently observed downward sloping nature of long-term forward rates

(beyond-10-year spectrum). They collect many evidence that this phenomenon is likely due to the hedge-role of longer-term securities against uncertainty.

Badshah et al. [2019] study the effect of two uncertainty indices (VIX, US EPU) on the stock-commodity correlations. Their finding is that economic policy uncertainty has a strong and positive effect on the correlations (for most commodities), while VIX seems to be insignificant when the economic conditions are not controlled for. This indicates that market volatility does not cover all the effects which are responsible for stock-commodity correlations. The correlations seem to be larger during weaker economic conditions for most commodities, as it is expected. An underlying economic explanation is that investors require a greater risk premium when policy uncertainty is high, and bad economic conditions enhance this motive. Some commodities (especially precious metals) are found to be good hedging instruments against uncertainty.

The work of Castelnuovo [2019] – to the best of my knowledge - is the closest in spirit to my research. He examines how the term structure of interest rates responds to a shock in financial uncertainty, using local projections analysis (LPA). The financial uncertainty is measured by the financial index of Ludvigson et al. [2019], the yield curve data are US Treasury Bills yields from 1962 to 2018 of both short- and long-term maturities (up to 10-years). Since inflation and the stance of the financial cycle play a crucial role in determining the yields, economic growth and inflation are controlled for. The results show that both short and long-term interest rates respond negatively to the shocks of financial uncertainty.³ However, the short end of the yield curve exhibits a stronger negative response, which implies that the curve becomes steeper after one standard deviation jump in uncertainty. He tests whether these observations can be related to short and medium-term expectations, and finds supportive evidence that output response is indeed peaking in the medium term.

How it can be decided whether the above described uncertainty measures are endogenously responding to other real or financial variables, or exogenously drives their variations (or the mixture of these)? For the sake of correct model specification, guidance is needed from the literature. Some theoretical and practical findings - and ambiguities - are reviewed in Bloom [2014] and Ludvigson et al. [2021].

In many cases, uncertainty in economic theory is defined as the time varying volatility of real activity indicators. This treatment inherently excludes the possibility of separately analyzing the effects of uncertainty movements. In other theoretical frameworks, uncertainty is essentially an exogenous source of variation, which exerts a countercyclical behavior and increases the variability of other economic fundamentals (Bloom [2009]). Further theories consider that

³A downright explanation of this again lies in the elevated savings under uncertain economic conditions. As the bond prices and yields are negatively related, cutting back spendings drives down the yields.

uncertainty is responding to lower real economic activities, by additionally amplifying risky behavior, altering the forecastability of the events or giving rise to novel policy solutions (Fostel and Geanakoplos [2012]; Fajgelbaum et al. [2017]; Pástor and Veronesi [2013]). Following from the aforementioned real options theory and precautionary savings motives, it also seems likely that uncertainty leads the variation in other series. Consequently, this lack of clear theoretical support can lead to arbitrarily specified models in empirical work. For example, in a vector-autoregressive framework, correct ordering of the variables is crucial.

Empirical results indicate that financial uncertainty is a likely cause, while macro or real uncertainty originates endogenously (Ludvigson et al. [2021]). An instrumental variable approach is given by Baker and Bloom [2013]. They use stock market moments as indicators for economic condition and some clearly exogenous uncertainty proxies, such as natural disasters, terrorist attacks and political shocks to construct a cross country panel data. The results show that the shocks of these proxies are valid instruments, so they exhibit predictive power and are drivers of the business cycle.

3 Methodology

3.1 The Diebold-Li model

The literature on interest rate and yield curve modeling is voluminous (see e.g. James and Webber [2000]). Due to space and structural considerations, I only provide description of the class of my selected method.

As the yield curves are theoretical constructs, they must be estimated from market data. The base-case for that is government bond yields – as these are considered free from individual risks –, but using interbank lending rates, future rates and swap rates sometimes might be better choices, due to their less noisy nature (Reppa [2008]). Once the unsmoothed yields are estimated, curve fitting techniques can be used for obtaining the continuous yield curves.

A highly nonlinear modeling approach is represented by curves of the Nelson-Siegel family, referred to as parametrically parsimonious models. With only using a few parameters, they can approximate curves with not too complex shapes. Originally, Nelson and Siegel [1987] assumed a particular shape for the forward rate curve, described by the following second order differential equation:

$$f_t(\tau) = \beta_{1t} + \beta_{2t}e^{-\lambda_t\tau} + \beta_{3t}\lambda_t\tau e^{-\lambda_t\tau}, \quad (1)$$

where τ represents the vector of maturities, f_t is the forward rate from time t to τ and λ_t , β_{1t} , β_{2t} , β_{3t} are shape parameters. The spot curve can be obtained by averaging through the forward curve.

The model is consistent with the factor interpretation of the yield curve and has gained a lot of recognition over the past decades. It is extensively used by policymakers and central banks for yield curve modeling (Bank of International Settlements [2005], European Central Bank [2008]). This family of curves has been modified by many authors. For example, Svensson [1994] extends the model with an additional exponential decay term, which extends its performance in capturing curves with more complex shapes.

An important refactorization and dynamic reinterpretation is due to Diebold and Li [2006], which I use in my study for obtaining my continuous yield curves. The model is extensively used in the literature due to its efficient and yet parsimonious nature (e.g. Shang [2022], Reppa [2009]). The model can be written as follows:

$$y(\tau) = \beta_{1t} + \beta_{2t} \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} \right) + \beta_{3t} \left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau} \right), \quad (2)$$

where τ is the vector of maturities, λ_t is the shape parameter and β_{it} are the factors to be estimated on the *cross-section* of yields.

The different factorization of Diebold and Li [2006] have at least two important benefits: *first*, an economic meaning can be given to the factors due to the shape of their loadings. The first latent factor, β_{1t} can be interpreted as level, due to its constant loading (equals to 1), so its impact on the yields is the same for all maturities. Its effect is the most pronounced in the long-term. The loading of β_{2t} , $f_1 = \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau}$ might be interpreted as slope: it is an exponential decay function, which mostly affects the short end of the yield curve. The loading of β_{3t} , $f_2 = \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}$ drives the humps/troughs of the curve and has the strongest effect at the medium-term. *Figure 1* illustrates these.

If $\beta_{2t} > 0$ ($\beta_{2t} < 0$), the curve slopes downwards (upwards). The sign of the curvature factor, $\beta_{3t} > 0$ ($\beta_{3t} < 0$) determines if there is a hump (trough) in the curve, and a higher absolute value entails a more pronounced curvature. The shape parameter, λ_t determines the steepness of the slope factor and the location of maximum (minimum) of the hump/trough. The three factors of the model correspond well to the empirical, data-based level, slope and curvature.⁴

A *second* important advantage of the DL model over the original NS model is that usually there is less multicollinearity present between the factor loadings, which improves the estimation.

I use fixed $\lambda_t = 0.0609$ parameter in my estimations the same manner as in Diebold and Li

⁴It can be shown, that the factors correlate strongly with their empirical counterparts: for example, level can be defined as $y(120) - y(3)$, slope as $y(120) - y(3)$ and curvature as $2 * y(24) - y(120) - y(3)$ (see e.g. Diebold and Li [2006]).

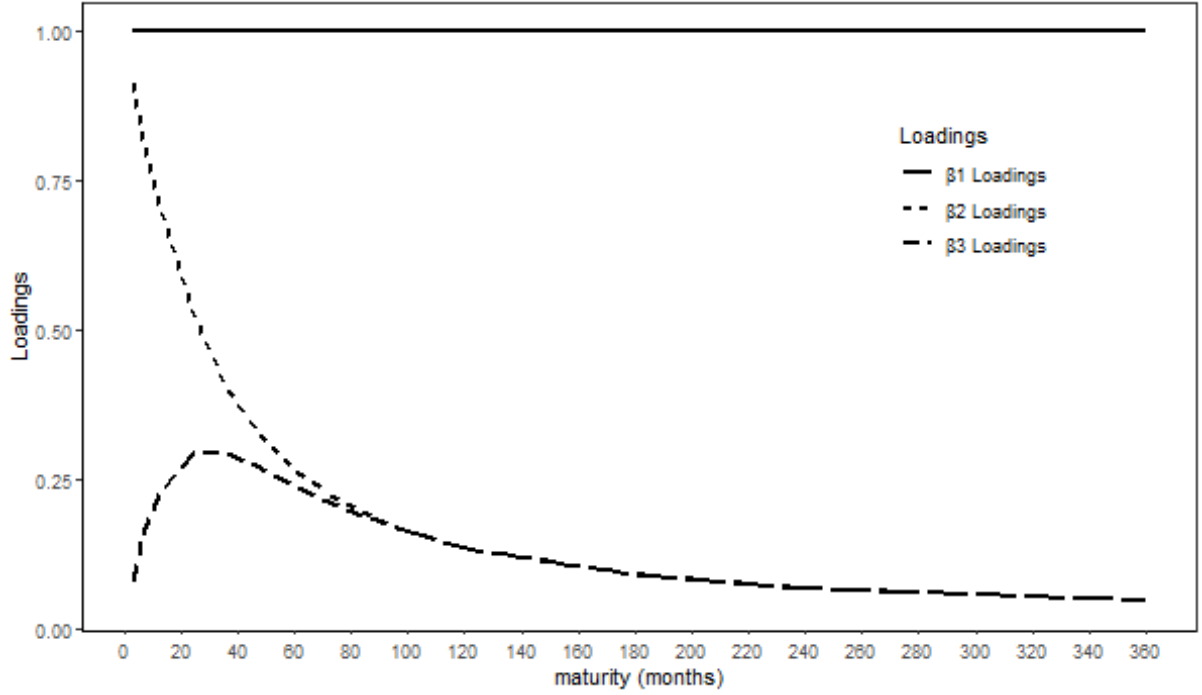


Figure 1: The three Nelson-Siegel factor loadings with $\lambda_t = 0.0609$. Diebold & Li (2006) reinterpreted the original NS factors as level, slope and curvature due to the shape of their loadings. The fixed $\lambda = 0.0609$ parameter maximizes the loading of the curvature factor at mid-term maturity (30 months).

[2006]. This solution reduces the dimension to three factors and makes the dynamic usage of the model possible. The fixed λ_t value forces the hump/trough of the curve to be at a specific maturity, at 30 months in this case. This choice is motivated by the observation that most humps and troughs are usually between the second and third year. Moreover, it brings the benefit of calculational convenience and trustworthiness. Since the DL model is highly nonlinear in nature, it is very sensitive to starting parameters and can easily stuck into local optima (e.g. Cairns and Pritchard [2001]). The fixed shape parameter solves this by reducing the calculations to simple ordinary least squares (OLS) estimations on the cross-section of yields. However, some scholars warn that multicollinearity can still be present, as it is dependent on the chosen maturity vector and shape parameter value (Annaert et al. [2010]; Valle et al. [2018]). Following from these considerations, I tested the correlation between the third and second factor loadings, which is 0.21 with my sample maturities (see Section 4 for details) and fixed shape parameter value, which I do not deem a calculational concern.

After fitting the model to the cross-section of yields for every available days in my sample period, the resulting time series of the factors can be used dynamically for yield forecasting or modeling.

3.2 Vector-autoregression

The second part of my estimation explores the dynamic relationships between uncertainty and the DL factors. For this purpose, I estimate p th order vector-autoregressive (VAR) models for the sample countries. The general reduced form representation is as follows:

$$y_t = \delta + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \dots + \Gamma_p y_{t-p} + U_t, \quad (3)$$

where y_t is the $m \times 1$ vector of the endogenous variables, δ is the $m \times 1$ vector of the constant terms, p is the optimal lag length number and $\Gamma_1, \Gamma_2, \dots, \Gamma_p$ are the estimated $m \times m$ transition matrices. Finally, U_t represent the vector of reduced-form residuals fulfilling $E(U_t) = 0$, $E(U_t U_t') = \Sigma_{UU}$ and $E(U_t U_s) = 0$ for $t \neq s$.

In my base-case models, $y_t = [\text{uncertainty}, L, S, C]'$, so the constructed system consists of four time series (an uncertainty index and the three estimated DL factors) for each sample country. I determine the optimal length of p with Akaike information criterion (AIC), setting the maximum lag length number to 5 months (as an utmost value of p for my sample size). The stability of the VAR(p) models requires the variables to be stationary, which property is inspected with the Augmented Dickey-Fuller (ADF) unit root test.

I conduct Granger-causality tests to gain some insights about the direction of the effects. For this purpose, only bivariate VAR models are used, containing an uncertainty index and the DL factors one-by-one. Granger-causality tests are used to determine whether one variable is useful for predicting the evolution of the other series. A Chi-square or F-test is used for calculating the joint significance of the lagged values of the other series.

Impulse responses and variance decompositions are popular metrics for analyzing the temporal dynamics of the interactions between the variables in the system. The calculation of both requires the moving average (MA) representation of the VAR(p) models. In order to obtain the orthogonal shocks resulting from the VAR models, some preliminary assumptions are needed about endogeneity/exogeneity. I use the standard Cholesky-decomposition method for identifying the structural equations, which imposes recursive restrictions on the residuals. Uncertainty indices are ordered first in each cases (which means they are assumed to be the exogenous series in the system). The IRFs essentially work as follows:

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}}, \quad (4)$$

so they show the effect of one standard deviation shock of time series j in time t on time series i in time $t + s$.

Variance decompositions show the contribution of the j th variable to the mean squared error

(MSE) of the s -period ahead forecast.

4 Data Description and Sample Period

4.1 Yield and Uncertainty Data

The four countries considered in my analysis are the United States, Japan, Germany and the United Kingdom (as a side note, Diebold et al. [2008] used these countries to extend the Diebold-Li model to a global context). All of them exhibit a high financial openness,⁵ and are important contributors to the world-level GDP. I use daily frequency zero coupon yield data with maturities of 3-month, 6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 6-year, 7-year, 8-year, 9-year, 10-year, 15-year, 20-year and 30-year.⁶ The sample period is from 4th January 2000 to 28th February 2020, so the effects of COVID-19 pandemic is mainly ruled out. Otherwise, substantial economic condition variations are present, the period includes two very significant stock-market downturns and two recessions. In order to make use of all the available yield data, I fit the continuous yield curves on daily cross-sections, and calculate the monthly average of the estimated factors. A further advantage of this solution is a smoother time series of the factors.

Figure 2 shows the evolution of the yields in Germany. It can be seen that most of the daily curves behave normally, so they slope upwards. A large variation in the slope is clearly visible: there is a flattening or downward sloping tendency in the period of the 2008 Great Recession. The temporal decrease in the level of yields is also visually apparent, a sign that the level factor is shrinking with time. The variations in the curvature factor can also be identified.

In *Table 1*, I present descriptive statistics for the yields and the empirical factors. The short-end of the term structure is generally more volatile than the long maturities. It is clear that the typical curves are upward sloping. Across the sample, the Japanese yields are remarkably lower than in the other countries.

⁵As measured by the KAOPEN index of Chinn and Ito [2008].

⁶The zero-coupon yield data is kindly provided by my supervisor via <https://Bloomberg.com>.

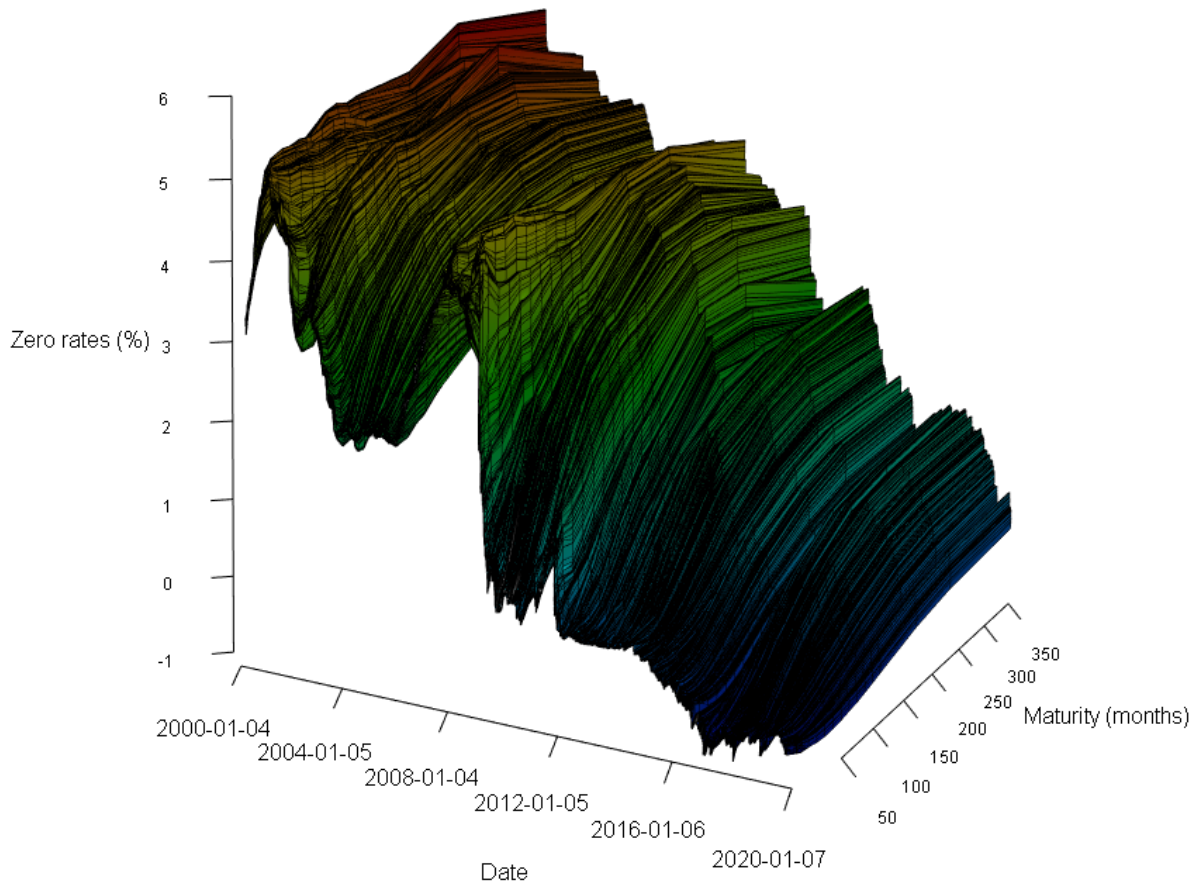


Figure 2: Evolution of the yield curve in Germany, daily frequency. Maturities of 3 months, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 6 years, 7 years, 8 years, 9 years, 10 years, 15 years, 20 years and 30 years are shown. *Source: own figure based on own calculations.*

Table 1: Descriptive statistics, yield curves

Maturity	Germany				Japan				United Kingdom				United States			
	Mean	Std.dev.	Min	Max	Mean	Std.dev.	min	max	mean	Std.dev.	Min	Max	Mean	Std.dev.	Min	Max
3-month	1.3379	1.8252	-1.051	5.070	0.0495	0.1961	-0.381	0.666	1.6945	1.8191	0.000	6.490	2.2395	2.1703	0.008	6.050
6-month	1.3889	1.8301	-0.981	5.140	0.0695	0.2041	-0.338	0.673	1.8030	1.8710	0.011	6.843	2.2910	2.2050	0.011	6.410
1-year	1.4492	1.8557	-0.984	5.242	0.0979	0.2433	-0.349	0.844	1.9050	1.8397	0.043	7.067	2.3356	2.1800	0.023	6.623
2-year	1.5638	1.8657	-0.954	5.334	0.1610	0.2989	-0.360	1.095	2.1339	1.7244	0.207	7.096	2.4887	2.1166	0.073	6.727
3-year	1.7240	1.8954	-0.975	5.354	0.2471	0.3503	-0.366	1.301	2.3761	1.6382	0.268	7.017	2.6644	2.0490	0.079	6.793
4-year	1.9044	1.9090	-0.970	5.377	0.3515	0.4101	-0.381	1.481	2.6100	1.5594	0.439	6.960	2.8089	1.9430	0.123	6.583
5-year	2.0438	1.8830	-0.954	5.387	0.4467	0.4638	-0.390	1.585	2.8274	1.4808	0.605	6.946	2.9308	1.8616	0.170	6.516
6-year	2.2024	1.8730	-0.913	5.467	0.5557	0.5054	-0.379	1.696	3.0151	1.4313	0.757	6.980	3.0391	1.7839	0.215	6.463
7-year	2.3566	1.8758	-0.883	5.632	0.6646	0.5549	-0.371	1.840	3.2027	1.3938	0.910	7.015	3.1444	1.7171	0.226	6.410
8-year	2.4819	1.8582	-0.835	5.705	0.7914	0.5999	-0.347	1.973	3.3484	1.3524	1.068	6.984	3.2380	1.6485	0.263	6.286
9-year	2.5812	1.8232	-0.783	5.682	0.8922	0.6266	-0.319	2.038	3.4657	1.3152	1.105	6.951	3.3202	1.5840	0.312	6.141
10-year	2.6714	1.7916	-0.732	5.752	0.9954	0.6594	-0.281	2.179	3.5466	1.2632	1.141	6.919	3.3915	1.5263	0.362	5.867
15-year	3.1106	1.7906	-0.524	5.930	1.3841	0.7143	-0.126	2.538	4.0668	1.3447	1.302	7.218	3.6479	1.3434	0.659	5.427
20-year	3.3372	1.8199	-0.387	6.476	1.6547	0.7105	0.011	2.745	4.2696	1.3449	1.504	7.203	3.7140	1.1866	0.890	5.267
30-year (level)	3.2946	1.6752	-0.234	6.483	1.9127	0.7561	0.038	3.310	4.2013	1.0446	1.707	6.669	3.6448	1.0851	0.951	5.059
slope	1.956	0.893	0.172	4.080	1.863	0.624	0.362	3.148	2.506	1.571	-0.757	5.157	1.405	1.780	-2.036	4.527
curvature	-1.504	0.763	-2.994	0.608	-1.640	0.576	-2.751	-0.352	-1.628	1.284	-4.347	2.050	-0.906	1.592	-3.646	3.251

Notes: The table provides descriptive statistics of the daily yield data (sample period: 2000:01:04-2020:02:28). The last three columns show the yield curve level, slope and curvature, defined as $y(360)$, $y(360) - y(3)$ and $2 * y(24) - y(3) - y(360)$, respectively.

The two uncertainty indices I use are the following: the three-horizon ahead version of (1) the global financial uncertainty index by Ludvigson et al. [2019] and (2) the global macroeconomic uncertainty index Jurado et al. [2015]. Both can be downloaded from <https://www.sydneyludvigson.com/data-and-appendixes>. See Section 2.1 for a detailed description. I plot the indices in *Figure 3*. It is clear that the spikes are related to crisis times (likely the dotcom bubble at beginning of 2000s, the 2008 Great Recession, the European migrant crisis starting at 2015 and the onset of the COVID-19 pandemic after 2020). The correlation between the two series is 0.66.

As Connolly et al. [2018] points out, in the case of macroeconomic uncertainty, Jurado et al. [2015] use the revised version of the underlying macro series, which makes it more reasonable to use the $t - 1$ values for estimating the effects of uncertainty in time t . For the sake of consistency and completeness, I also estimate the models with using end-of-month yield data and by monthly averaging from second half of month t until the middle of month $t + 1$. The results of these are discussed in the section "Robustness of the results", together with alternative model specifications.

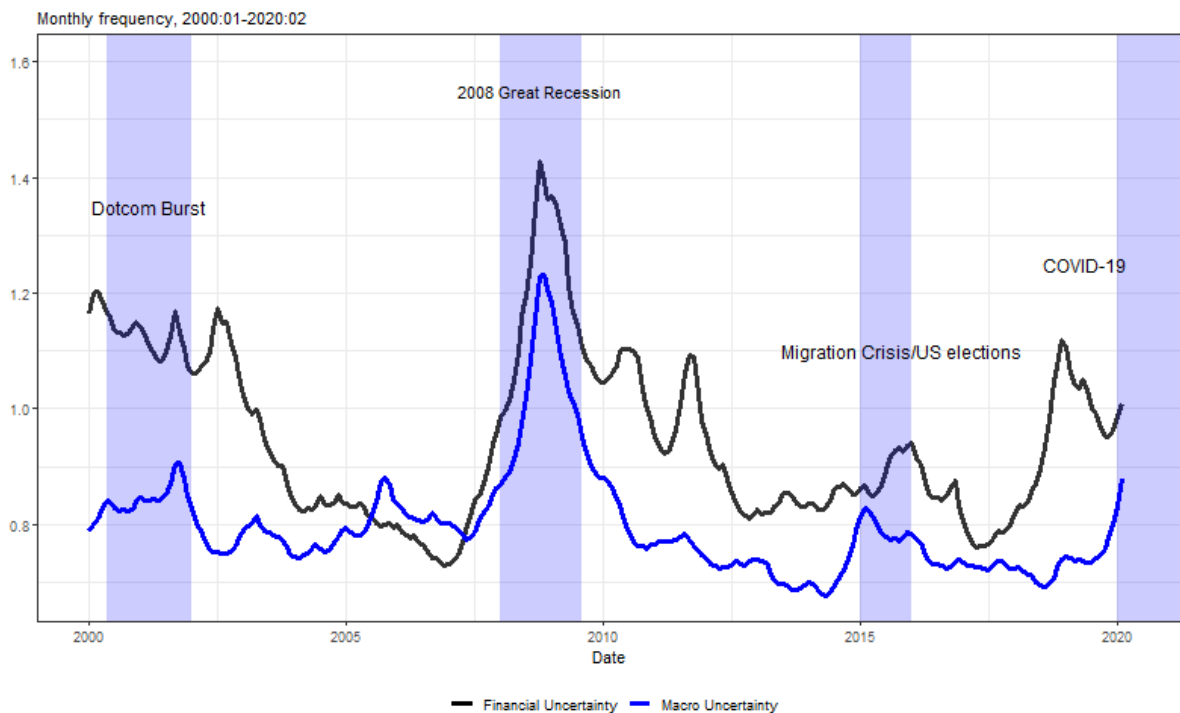


Figure 3: Financial and Macroeconomic uncertainty as measured by Jurado et al. [2015] and Jurado et al.[2019].

4.2 Macroeconomic Variables

The inflation and industrial production data are supposed to capture supply and demand shocks. I downloaded the series from the OECD database. The industrial production is in percentage relative to 2015 (2015 = 100), while the inflation data show the year-on-year annualised growth rate (with base rate = 2015) of consumer prices. A minimum requirement for capturing the basic macroeconomic dynamics would also call for a proxy for monetary policy instrument (e.g. Diebold et al. [2006], Reppa [2009]). Unfortunately, the time series of the key monetary policy rates are hard to use reliably for inference statistics in big parts of my sample period (for example, the Japanese rate was on the zero-lower bound for almost five years from 2001 to 2006). Furthermore, solely the central bank rate movements can not account sufficiently - and might lead to biases - for the impact of the monetary policy, as it does not incorporate the unconventional tools at the ZLB periods. Therefore, I do not include any metrics for monetary policy shocks in my analysis.

5 Findings

5.1 Results of Diebold-Li model estimation

This subsection summarizes the results of the yield curve fitting based of equation (2). I plot the time series of the daily estimated factors in *Figure 4*. The level factor slopes downward in each countries, indicating that the yields are decreasing with time. As the yield movements are constrained by the zero lower bound, the level factor should not cross zero.

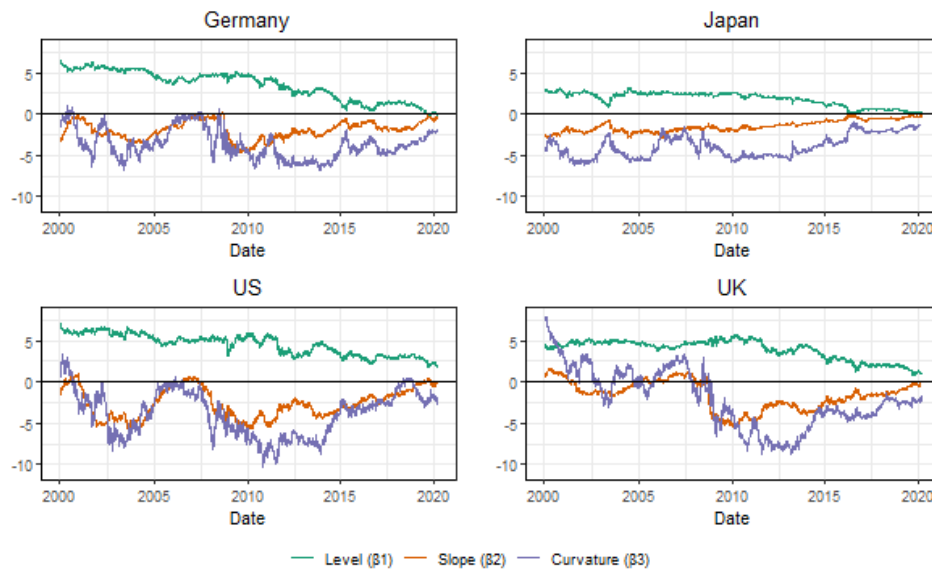


Figure 4: Time series of the daily estimated level, slope and curvature factors in the sample countries. The negative values of β_{2t} implies a positively sloped (normally behaved) yield curve. *Source: own figure based on own calculations.*

The root-mean-square-error (RMSE) values of the daily estimations (to all maturities) are 0.1278, 0.1712, 0.1514 and 0.1348 in Germany, Japan, US and UK respectively. The estimation accuracy is decreasing at the long-end of the curve, as the data points are getting less dense. Since long maturity calculations might degrade the overall goodness-of-fit, the detailed RMSE values of the various maturities are also presented in Table 2.

As we go beyond the 10-years spectrum of the yield curves, the model's performance abruptly degrades in most sample countries. Interestingly, the efficiency is relatively lower on the very short-end (3-month maturity) of the curves as well. *Figure 5* visually illustrates these results in the United Kingdom.

Table 2: Detailed RMSE values of the various maturities

Maturity	Germany	Japan	United Kingdom	United States
3-month	0.1377	0.1666	0.158	0.1234
6-month	0.0327	0.0165	0.0609	0.0454
1-year	0.1471	0.1719	0.162	0.1495
2-year	0.1515	0.2236	0.16	0.1669
3-year	0.0765	0.1311	0.0748	0.1046
4-year	0.0428	0.0318	0.063	0.0557
5-year	0.0899	0.0973	0.0887	0.0735
6-year	0.1143	0.1553	0.1204	0.1147
7-year	0.117	0.1916	0.1197	0.138
8-year	0.1095	0.181	0.1114	0.1341
9-year	0.1038	0.1682	0.0979	0.1212
10-year	0.0953	0.1532	0.1168	0.1043
15-year	0.1559	0.0785	0.2195	0.1165
20-year	0.228	0.2029	0.2622	0.169
30-year	0.1727	0.3345	0.2544	0.2605

Notes: The table presents the detailed RMSE values of the Diebold-Li model fitting using daily yield data 2000:01:04 - 2020:02:28 ($\lambda = 0.0609$). *Source:* Own table based on own calculations.

The descriptive statistics of the monthly averaged factors are presented in *Table 5* in the Appendix. The last three columns show the autocorrelations calculated at 1, 12 and 30 months. However, all series exhibit a strong persistence (the one-month lag autocorrelation generally exceeds 0.95), the level factor is the most, while the slope (spread dynamics) and curvature is much less persistent.

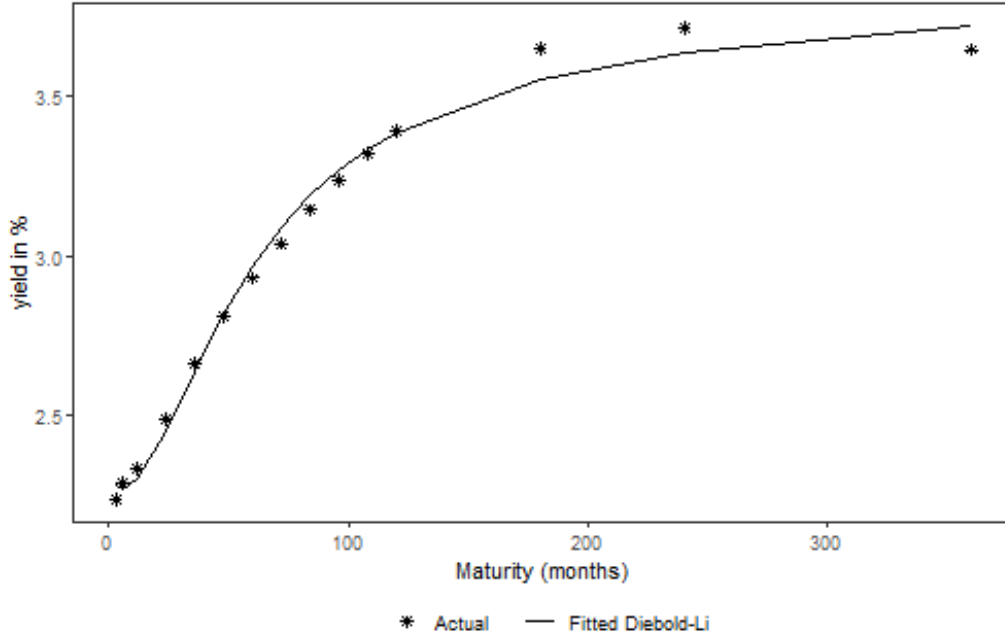


Figure 5: Actual and fitted average yield curve in the United Kingdom. The average actual data points are the mean values of the yields of given maturities in the sample period 2000:01:04 - 2020:02:28. The average fitted (model-based) curve is obtained by estimating the Diebold-Li model at the mean values of $\hat{\beta}_{1t}$, $\hat{\beta}_{2t}$, $\hat{\beta}_{3t}$. *Source: own figure based on own calculations.*

The Augmented Dickey-Fuller test results are summarized in *Table 3*. In case of the estimated level ($\hat{\beta}_{1t}$) factors, a trend is clearly present in each sample countries. As the stationarity of all components is essential for VAR model stability and estimation consistency, I detrended the series of the level factor. As a side note, although economic theory also suggests highly persistent bond yields, they should not have unit roots, because they are constrained from below by the ZLB. Since unit-root processes have random walk components, they will eventually cross zero. Despite these, random walks (unit-roots) are a well approximation of yield movements as long as they are not too close to zero (see e.g. Jardet et al. [2013]).

I do not perform any transformation on the second and third factors. The ADF tests suggest that no unit root is present either with the test specifications without drift and trend (None) or when only drift is included. Although the p-values are usually smaller in the equation with drift and trend, the coefficient of the trend term in the test regressions is either statistically insignificant or negligably small.

Table 3: Summary of the Augmented Dickey-Fuller tests.

	None	Drift	Drift and trend
Germany			
Level ($\hat{\beta}_{1t}$)	0.0676*	0.7633	0.0080***
Slope ($\hat{\beta}_{2t}$)	0.146	0.0290**	0.0251*
Curvature ($\hat{\beta}_{3t}$)	0.2441	0.0016***	0.0025***
Japan			
Level ($\hat{\beta}_{1t}$)	0.1328	0.3410	0.0166**
Slope ($\hat{\beta}_{2t}$)	0.0720*	0.0880*	0.0007***
Curvature ($\hat{\beta}_{3t}$)	0.3183	0.0834*	0.0086***
United States			
Level ($\hat{\beta}_{1t}$)	0.1784	0.1809	2.80e-05 ***
Slope ($\hat{\beta}_{2t}$)	0.2650	0.0597 *	0.0385 **
Curvature ($\hat{\beta}_{3t}$)	0.1950	0.00334***	0.0042**
United Kingdom			
Level ($\hat{\beta}_{1t}$)	0.2956	0.9194	0.0384**
Slope ($\hat{\beta}_{2t}$)	0.1550	0.0382**	0.0789*
Curvature ($\hat{\beta}_{3t}$)	0.0633*	0.0074***	0.0250**
Financial Uncertainty	0.459	0.00247***	0.00414**
Macroeconomic Uncertainty	0.903	0.000345***	0.000406***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: I present the p-values of the ADF tests with three types of specifications: with drift and trend term, with only drift term and with none of them included.

5.2 Uncertainty with yields-only model estimation results

All the results presented in this section are based on the VAR specification described by equation (3) and all changes will be indicated.

5.2.1 Causality directions

Before turning to the examination of my main research question, I briefly describe the results of the Granger-causality tests. Although, more sophisticated methods are presented in Ludvigson et al. [2021] or Baker and Bloom [2013], Granger-causality can still to some extent inform about the causal directions between uncertainty and the term structure of interest rates (Castelnuovo [2019]). The bivariate VAR models are estimated with the possible combinations of each uncertainty indices and latent factors used in the paper. *Table 4* shows the results of the calculations.

The results point to slight evidence in favor of Granger-causality going from uncertainty to

Table 4: Results of the Granger-Causality tests.

Null Hypothesis	F-Statistic	p-value	Direction
Germany			
Macro Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	5.8856	0.00059***	UNC $\Rightarrow \hat{\beta}_{1t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	5.4288	0.001121***	UNC $\Leftrightarrow \hat{\beta}_{2t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	1.6082	0.1202	UNC $- \hat{\beta}_{3t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	3.5595	0.0143**	UNC $\Rightarrow \hat{\beta}_{1t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	5.5996	0.00088***	UNC $\Leftrightarrow \hat{\beta}_{2t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	2.3566	0.09586*	UNC $\Rightarrow \hat{\beta}_{2t}$
Japan			
Macro Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	3.6915	0.01196*	UNC $\Rightarrow \hat{\beta}_{1t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	3.106	0.02632**	UNC $\Rightarrow \hat{\beta}_{2t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	2.347	0.07204*	UNC $\Rightarrow \hat{\beta}_{3t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	0.8507	0.4278	–
Financial Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	1.4497	0.2357	–
Financial Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	1.865	0.1347	UNC $\Leftarrow \hat{\beta}_{3t}$
United States			
Macro Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	6.2247	6.96e-05***	UNC $\Rightarrow \hat{\beta}_{1t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	1.9741	0.09739*	UNC $\Leftrightarrow \hat{\beta}_{2t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	1.627	0.1823	–
Financial Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	7.4154	7.344e-05***	UNC $\Leftrightarrow \hat{\beta}_{1t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	2.5704	0.006873***	UNC $\Leftrightarrow \hat{\beta}_{2t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	5.9164	0.0029***	UNC $\Rightarrow \hat{\beta}_{3t}$
United Kingdom			
Macro Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	4.6791	0.003126*	UNC $\Rightarrow \hat{\beta}_{1t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	9.3744	5.013e-06***	UNC $\Leftrightarrow \hat{\beta}_{2t}$
Macro Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	3.8708	0.004191***	UNC $\Leftrightarrow \hat{\beta}_{3t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{1t}$	3.5561	0.01437**	UNC $\Leftrightarrow \hat{\beta}_{1t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{2t}$	4.8019	0.008621***	UNC $\Rightarrow \hat{\beta}_{2t}$
Financial Uncertainty does not Granger Cause $\hat{\beta}_{3t}$	6.0766	0.00248***	UNC $\Rightarrow \hat{\beta}_{3t}$

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: I present the results of the Granger-Causality tests resulting from the bivariate VAR models. I only show the F-statistics and the corresponding p-values when the uncertainty metrics are the independent variables, but the Direction column shows when reverse causality is present ($p < 0.1$).

the latent factors. It can be seen that almost exclusively either bidirectional causality is present or from uncertainty to yields (the only reverse direction is in case of the Japanese curvature factor). These results are more in line with those of other authors' who suggest that uncertainty emerges rather exogenously (e.g. Bloom [2009], Baker and Bloom [2013], Castelnovo [2019]) or stating its mixed source (Ludvigson et al. [2021]), than with those of advocating its endogenous nature (Bachmann et al. [2011]). My findings here lend weak support that uncertainty should be ordered first in my subsequent models.

5.2.2 Financial Uncertainty shocks

Figure 6 shows the impulse response of the modelled DL factors to a one standard deviation shock of financial uncertainty. The level factor (defining the long-end of the term structure) abruptly drops after an upward variation in financial uncertainty in all sample countries. However, in case of the United States and United Kingdom, the fast decrease of level is followed by an overshoot between the 1 and 2 years horizon, before returning back to the steady-state. The magnitude of the responses seems to be similar, however, for the UK, the confidence band indicates insignificant jumps.

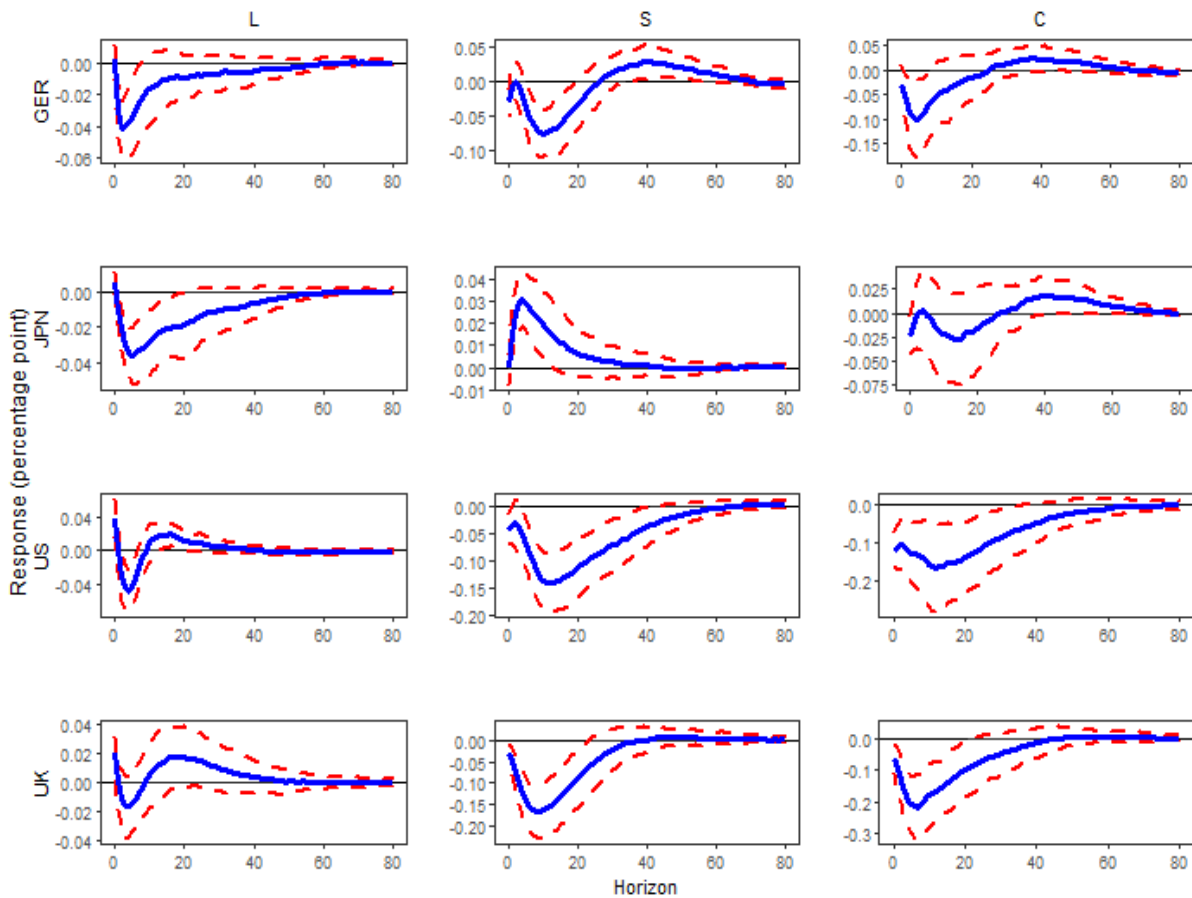


Figure 6: Impulse response (percentage point) of the factors to a one-standard deviation shock of financial uncertainty, as measured by Jurado, Ludvigson & Ng (2019). Point estimates identified by the solid blue lines, the red dashed lines indicate the 68% bootstrapped confidence bands. *Source: own figure based on own calculations.*

The behavior of the slope factor (which mainly affects the short-term yields) is less similar across the sample. A negative response implies more positively, an upward jump entails less positively sloped yield curves. In Germany, the peak negative response is observed roughly after 15 month, then it recovers and moderately overshoots. The factor in Japan exhibits an interesting behavior: after uncertainty rises, the factor increases (the yield curve becomes less steep). Finally, the second factor's behavior is very similar in the United States and the United

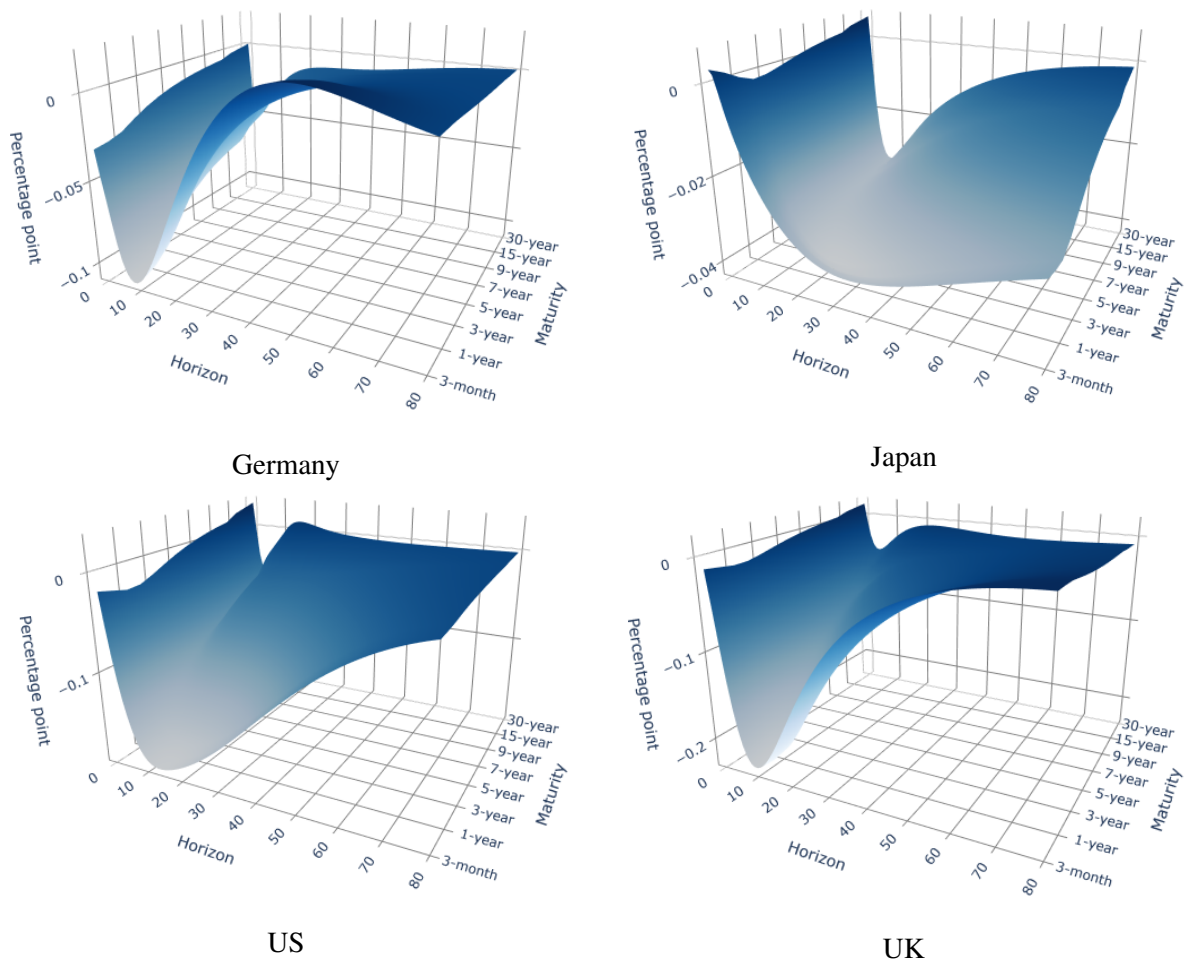


Figure 7: Impulse response of the yield curves in the sample countries to a one-standard deviation shock of financial uncertainty, as measured by Ludvigson, Ma & Ng [2019]. The response of the curves is constructed by multiplying the point estimates presented in Figure 6 with the loadings of the Diebold-Li factors. *Source: own figure based on own calculations.*

Kingdom both in shape and magnitude. In both cases it is peaking with -0.15 percentage points after about 15 months (a sign of a widening spread between the near-term and long-term yields). The curvature factor (mainly mid-term yields) drops in all cases, but with noticeable differences in magnitude. While in Japan it reacts insignificantly, in the other sample countries the decrease is more pronounced, which translates to less humped yield curves. The IRFs of the three latent factors can be used to construct the responses of the whole yield curves. The combined behavior of the individual factors is presented in *Figure 7*.

All the curve responses converge back to zero - although, slower in the near-term -, meaning that the effect of the shocks are temporary. It is immediately apparent that the short-end of the curves has a stronger negative response to increased financial uncertainty. The only exception to that is Japan, where the positive reaction of the slope factor causes a more flattened response. However, even here the short-term rates still exhibit a delayed convergence to their steady-state.

The behavior of yield curves reinforces that increased financial uncertainty implies a tem-

porary steepening of the yield curves. These observations are in line with those of Castelnovo [2019].

Table 6 (Appendix) provides variance decompositions of the Diebold-Li factors at 1-, 6-, 12-, 36-, and 60 months horizons. At the shortest horizon, very little of the variation in the factors is driven by financial uncertainty. In case of the level factor, even at a 60-month horizon, financial uncertainty accounts for only 5-6% of the variation in all countries. This suggests that the long-end of the yield curve remains relatively unaffected when unpredictability surrounds the economy. However, uncertainty largely contributes to the second and third factors' variance. Although, at 1-month horizon, less than 1% is explained from the slope, the effect of financial uncertainty quickly becomes influential (at a 5-years horizon, it accounts for more than 30% of the variation in the US and UK, almost 15% in Germany and roughly 9% in Japan). The explained variance from the curvature factor shows a high variability across the sample countries. It remains moderately influential in Germany and Japan (barely exceeds 4% even at the 60-months horizon), but in case of the US and UK, a substantial chunk of the variation is explained (accounts for well above 20% of the variance at the 36-months horizon).

Before turning to the economic implications and underlying mechanisms of the findings presented here, I briefly summarize - in a similar manner - the outcomes of the VAR estimations with macroeconomic uncertainty.

5.2.3 Macroeconomic Uncertainty shocks

How do the factors and the yield curve behave after a *macroeconomic* uncertainty jump?

Figure 8 exhibits the impulse responses of the individual factors and their aggregated behavior is shown in *Figure 9*. For the first sight - and somewhat expectedly, given the tight correlation of the indices -, the differences are only marginal compared to financial uncertainty shocks. Nevertheless, some clear distinctions can be noticed. The middle-horizon (15-20 months) overshoot of the level factors is discernible and greater for macroeconomic uncertainty jumps. Another difference can be seen in the slope factor movement in Japan, which was pushed up by financial and drops by upward variations in macroeconomic uncertainty (the yield curve gets less positively sloped in the first case, and steeper in the latter). Finally, the response of the curvature is more moderate (in absolute terms) for macro uncertainty shocks, so it produces less humped yield curves.

How do these effects aggregate? Similarly to financial, elevated macroeconomic uncertainty also results in decreasing yields of every maturities, as *Figure 9* confirms.

The variance decompositions of the macroeconomic uncertainty model are presented in *Table 7* in the Appendix. Macroeconomic uncertainty explains significantly more from the

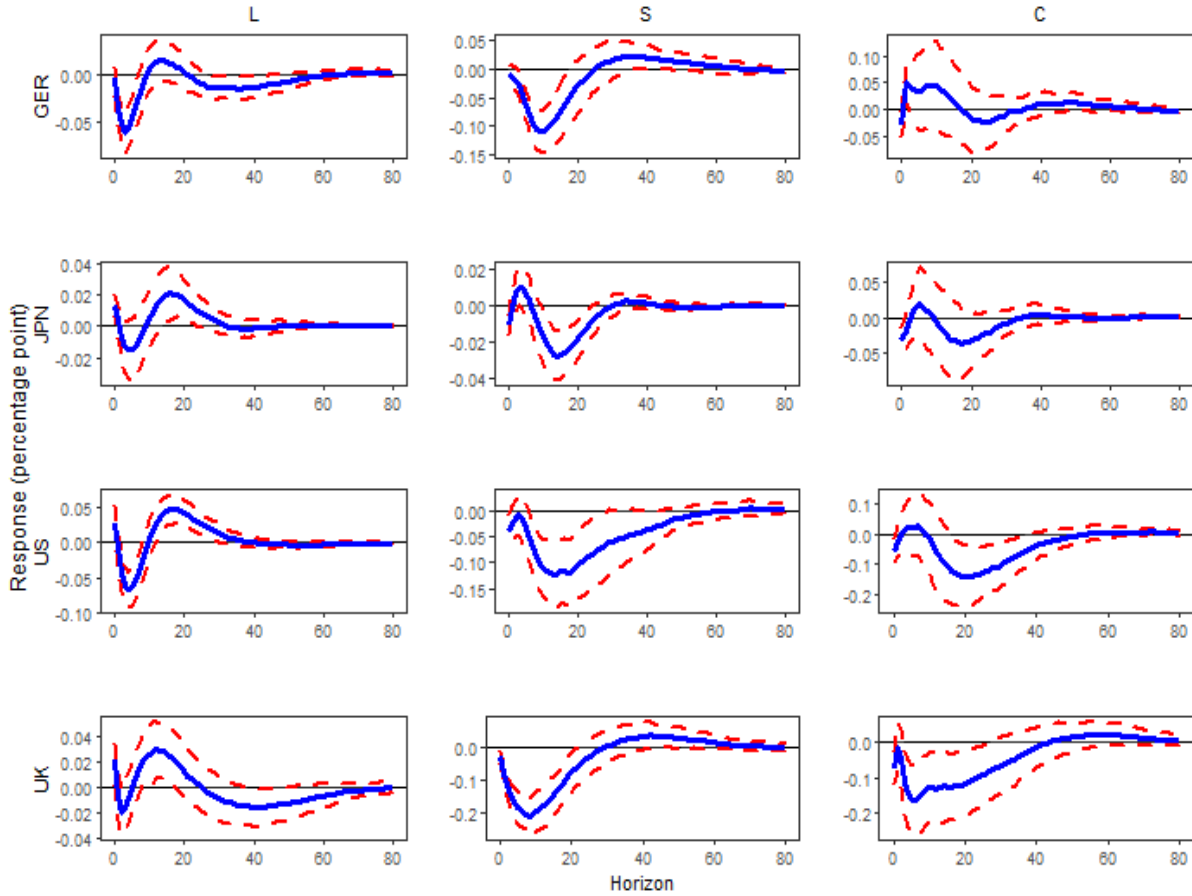
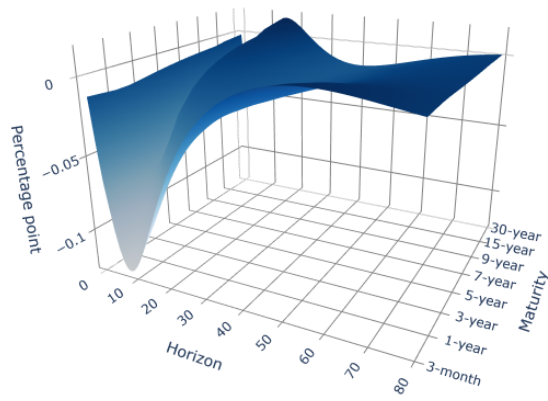
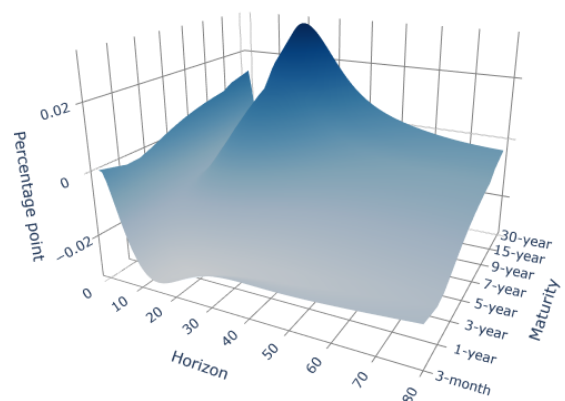


Figure 8: Impulse response (percentage point) of the factors to a one-standard deviation shock of macroeconomic uncertainty, as measured by Jurado, Ludvigson & Ng (2015). Point estimates identified by the solid blue lines, the red dashed lines indicate the 68% bootstrapped confidence bands. *Source: own figure based on own calculations.*

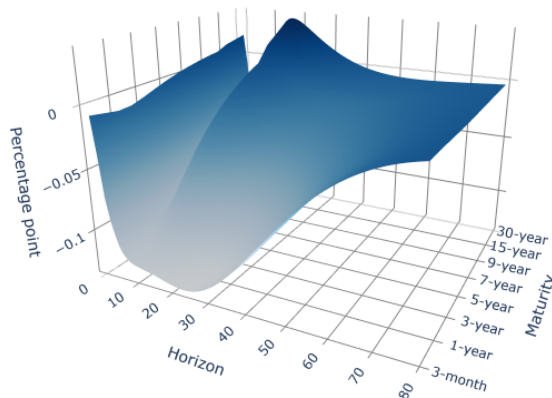
variation of the level factor in the US and UK than financial uncertainty (17.5% vs. 5.6% in the US and 9.5% in the UK at 60-month horizon) at longer horizons and slightly more in case of the other countries. Macroeconomic uncertainty is found to have a very strong predictive power on the slope factor in the UK: at 6-month, it accounts for almost 25%, and more than 55% of the variation at 1-year horizon. Contrary to financial, the second factor is highly explained by macroeconomic uncertainty in Japan and Germany (around 30% at 36-month for both), and powerfully explains the variation in the US as well. The variation in the curvature factor is slightly less accounted for by macroeconomic uncertainty than its financial counterpart in the US and Germany (roughly 16-18% and 1-1.5%) and is significantly more in Japan (8.8% and 12% at 3- and 5-years horizon). The two types of uncertainty explains the same amount of the variation in the UK.



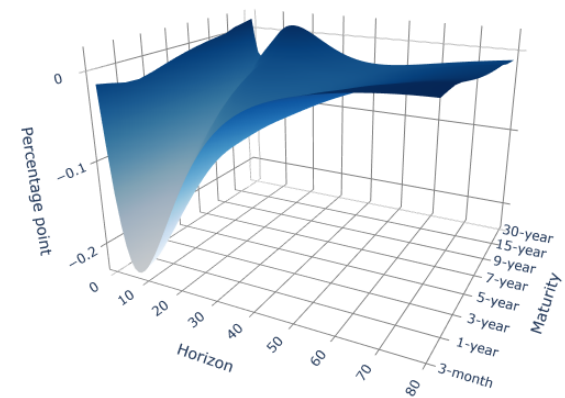
Germany



Japan



US



UK

Figure 9: Impulse response of the yield curves in the sample countries to a one-standard deviation shock of macroeconomic uncertainty, as measured by Ludvigson, Ma & Ng (2015). The response of the curves is constructed by multiplying the point estimates presented in Figure 8 with the loadings of the Diebold-Li factors. *Source: own figure based on own calculations.*

After analyzing the uncertainty-induced yield movements, we can summarize the observed effects as follows:

- [1] All yields drop after a shock of both types of uncertainty;
- [2] The short-maturity yields react more strongly.

An additional finding is that the Japanese factor/yield behavior is very dissimilar in terms of observation [2] compared to the other sample countries. Namely, the yield curve does not steepen as much.

How does economic theory support these results? [1] *Why all the yields decrease after uncertainty shocks?* [2] *Why do the yield curves get steeper?* As emphasized earlier, elevated uncertainty motivates precautionary savings, which in turn drives up bond prices - due to increased demand - and lowers yields. It clearly answers [1], but not necessarily [2]. However, it

is possible that investors are shortening the maturity of their portfolios under high uncertainty regimes. As the model of Bianchi et al. [2018] states, long-term bonds provide less protection against inflationary risk. Another downright mechanism is related to the close link between uncertainty jumps and economic downturns. Due to this connection, uncertainty triggers interest rate cuts by the monetary authorities, which is shown to have a very strong effect on the factors/yields (especially on slope/short-term yields) in many countries and typically steepens the yield curve (Diebold et al. [2006], Shang [2022], Castelnuovo [2019], Reppa [2009] amongst others). Ample of evidence indicate that the extent to which monetary policy generates effect [1] and [2] is strongly dependent on the zero-lower bound (ZLB) periods (for example Shang [2022], Morita [2015]).⁷ Since monetary policy rates typically emerge from a Taylor-type rule, the yield responses are also related to agents' expectations about future output growth and inflation. If increased uncertainty comes with a worse outlook on future growth or lower inflation, the expected monetary response is enough to drive down the yields. Moreover, it can be assumed that rational agents use similar rules when anticipating monetary actions. Medium recovery of growth rates following uncertainty shocks results in higher long-rates (Castelnuovo [2019]).

What are some possible explanations behind the different yield curve/factor reactions observed in Japan? Firstly, Japan was on the zero lower bound for big pieces of the selected period and is called the front-runner of unconventional monetary policies. Namely, the first ZLB lasted from 1999Q1 - 2000Q2, the second from 2001Q2 - 2006Q2 and the Bank of Japan conducted quantitative easing (QE) these times (e.g. Kimura and Nakajima [2013]). Later, the key rate of Japan was again set to almost zero (0.1%) after the collapse of Lehman Brothers in the end of 2008 and is -0.1% from 2016Q3 until now.⁸ During QE periods, the long-rates are targeted by the central bank. ZLB is shown to have considerable effect on the interest rate reactions to monetary actions in Japan (Morita [2015]). This explanation of the dissimilarities in effect [2] seems strongly plausible - the literature on the combined effects of uncertainty and ZLB (Caggiano et al. [2014], Basu and Bundick [2017]).

Another possible explanation might be that the Japanese rates are hit more by domestic uncertainty and the usage of the global index is not appropriate for evaluating their case. This explanation might hold, as Japan exhibits a very low trade openness throughout my selected period.⁹

⁷Interestingly, when the ZLB is effective, uncertainty itself makes the level and curvature more sensitive to monetary policy surprises (Shang [2022]).

⁸The Bank of Japan introduced the "comprehensive monetary easing policy" in the end of 2010. It decreased the target level of short-term key rates to 0.1 percent and committed itself to maintaining the virtually zero interest rate level until the price stability is reached. A quantitative and qualitative easing (QQE) policy started at 2013Q1 (Nakaso [2017]).

⁹See: https://www.theglobaleconomy.com/rankings/trade_openness/. Japan had the lowest export plus import per GDP from 2000 to 2004.

5.3 Rolling window analysis

I employ a rolling window over the period 2000:01 - 2020:02 with a window width of 7 years (84 months). Under each window, a VAR model is estimated in the same way as described by equation (3), which allows me to discover the dynamics of the previous findings.

Figure 10 and Figure 11 show the 6-month horizon impulse responses of the 3- and 120-month maturity yields to a one-standard deviation shock of financial and macroeconomic uncertainty. When the solid line is above the dashed, the long-maturity yields' response is weaker compared to that of the short-maturities' (steepening). I am focusing on the periods when the opposite happens, so when the yield curve is flattening after uncertainty shocks.

In Japan, the negative reaction of the 120-month rate quickly surpasses the fall of the 3-month rate for financial uncertainty shocks. Another shift is found in the window starting from 2010:01. It confirms the previous findings, that the steepening of the yield curve was observed to be less pronounced in the country. The spread dynamics for financial uncertainty strongly suggests that ZLB is intimately related to the occurrence of observation [2] after financial uncertainty shocks.¹⁰ The yield responses differences are narrowing as the ZLB period with QE

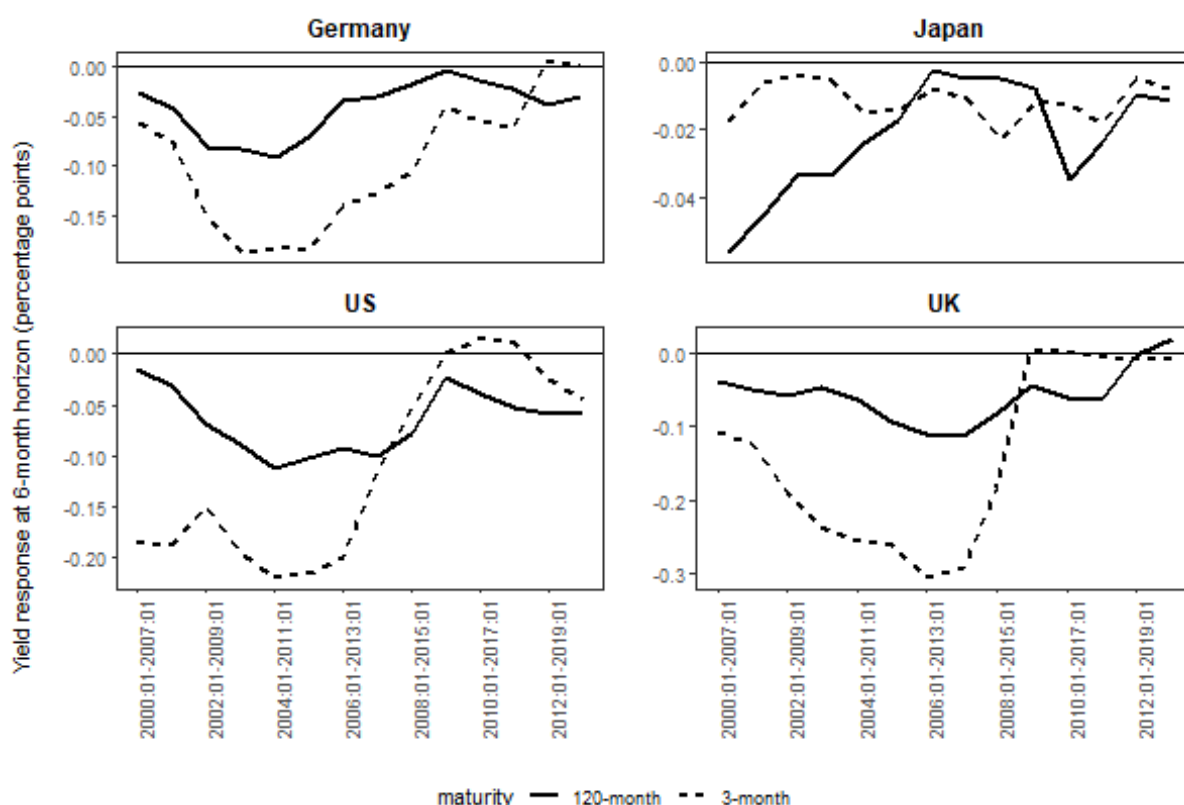


Figure 10: Impulse response of the 3-month and 120-month yields at half-year horizon in the sample countries to a one-standard deviation shock of financial uncertainty as measured by Jurado et al. [2019]. The lines connect the estimated responses in each of the 7-years long subperiods. *Source: own figure based on own calculations.*

¹⁰It should be noted that more effective methods exist to explicitly link the given responses to differently

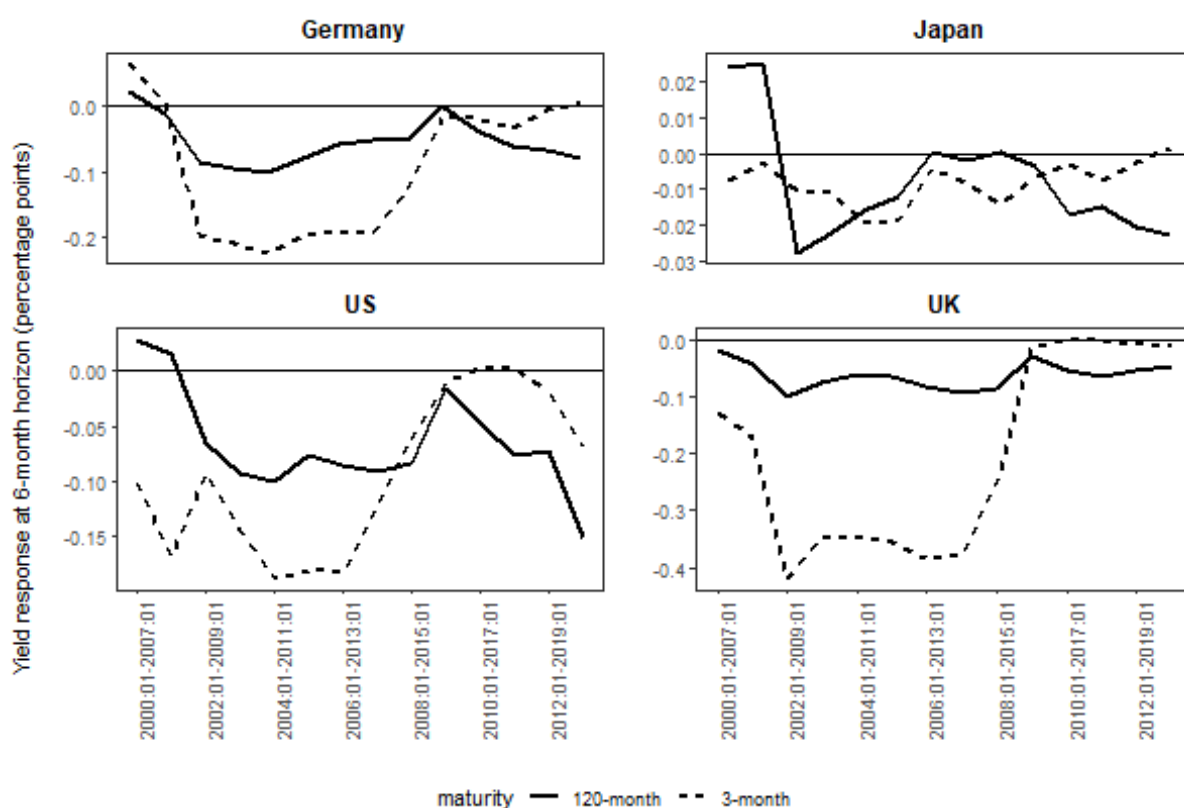


Figure 11: Impulse response of the 3-month and 120-month yields at half-year horizon in the sample countries to a one-standard deviation shock of macroeconomic uncertainty as measured by Jurado et al. [2015]. The lines connect the estimated responses in each of the 7-years long subperiods. *Source: own figure based on own calculations.*

gets less weight in the estimation windows.

Interestingly, the same relation does not hold for macroeconomic uncertainty in the first few windows (in fact, the 120-month yield responds highly positively). Maybe Japan reacted very differently to macroeconomic uncertainty, or maybe its very low trade-openness or other qualities in that period unjustifies the use of the world-level macro index.

In Germany, US and the UK the curves change positions almost under the same window (for both indices). Following the shift, the 120-month yield's reaction remains very close, but above to that of the short-rate's (the slope barely changes). Let's see the ZLB periods in these countries. In the US, the ZLB period is from 2008 to 2015 (the Fed has implemented QE in 2008, 2010 and 2012).¹¹ The Bank of England adjusted the policy rate to 0.5% at 2009Q1 and kept there until 2016Q3, when it was lowered to 0.25%. In Germany, the key rate was gradually

characterized regimes (for example by introducing nonlinearities into a VAR framework, as in e.g. Morita [2015], Shang [2022]). The 84-month window size I use is too long to separately analyze downturns and/or ZLB periods or other events, but shorter windows would degrade the estimation. However, it provides support in favor of the findings which explains ZLB impact on slope.

¹¹In particular, the Fed has conducted three rounds of large-scale asset purchases and provided systematic forward guidance about the future path of monetary policy. In Dec 2008, the US, the Federal Reserve cut interest rates to between 0% and 0.25%. Interest rates stayed at 0% as unemployment rose from 7.3% to 10% at the end of 2009. Between December 2008 and 2013, the US had been at this zero lower bound of monetary policy.

decreased from 1% in 2012 to 0% by 2016Q1 and remained.¹² In these countries, it can also be suspected that the ZLB plays the main role in the spread behaviors. The response of the short-end of the curve clearly moves closer - and eventually gets less sensitive than the long-end, as the windows are gliding forward to the ZLB - or very low interest rate - periods. Interestingly, in Germany, the 3-month yield's response to macroeconomic uncertainty (*Figure 11*) is more positive in the first two windows.

The varying pattern of yield curve reactions (at the 6-month horizon) under the different windows point to evidence in favor that monetary authorities play a great role in effect [2] or the slope factor's response to uncertainty shocks. When the central banks have the conventional tools to respond to the fluctuations in uncertainty, the steepening of the yield curves seems more likely to occur. On the contrary, when the monetary authorities are binded in their actions - having zero or limited ability to lower the key rates - the long-end of the term structure becomes more sensitive to uncertainty shocks than the short-rates.

5.4 Uncertainty with yields-macro model estimation results

Expected output growth and inflation crucially determines monetary policy actions and investor's decisions. Moreover, a close link exists between these macroeconomic variables and the level and slope factor (Diebold et al. [2006]). Given these important ties, I extend my previous models with industrial production and inflation. My goal is to collect further evidence in favor of certain mechanisms behind uncertainty-yield curve/factors interactions. As two additional variables are added now to the VAR framework described by equation (3), the estimated system might be too large (if the optimal number of lags are high), which can degrade the estimation. With the aim to improve model performance, I test whether the first two factors are sufficient to explain the *dynamic* yield curve evolution. *Figure 12* justifies the use two factors, as in all sample countries the cumulative proportion of variance explained by the first two principal components well exceeds 95%.

It should be noted that the figure does not imply that two factors are enough to describe the curves on the *cross-section* of data. So, although excluding the third factor might result in poorer fit on given days, it does not change much on the explanation of the yield curve *dynamics*. In other words, the change of the curvature factor from one day to another would add very little to the variation of the dynamic evolution of the yield curve. Consequently, it might worth to leave it out in an "exchange" of improved model estimation. *Figure 13* verifies that the first two principal components can indeed be interpreted as level and slope.

¹²Germany applies the ECB rates since the beginning of the 2000s.

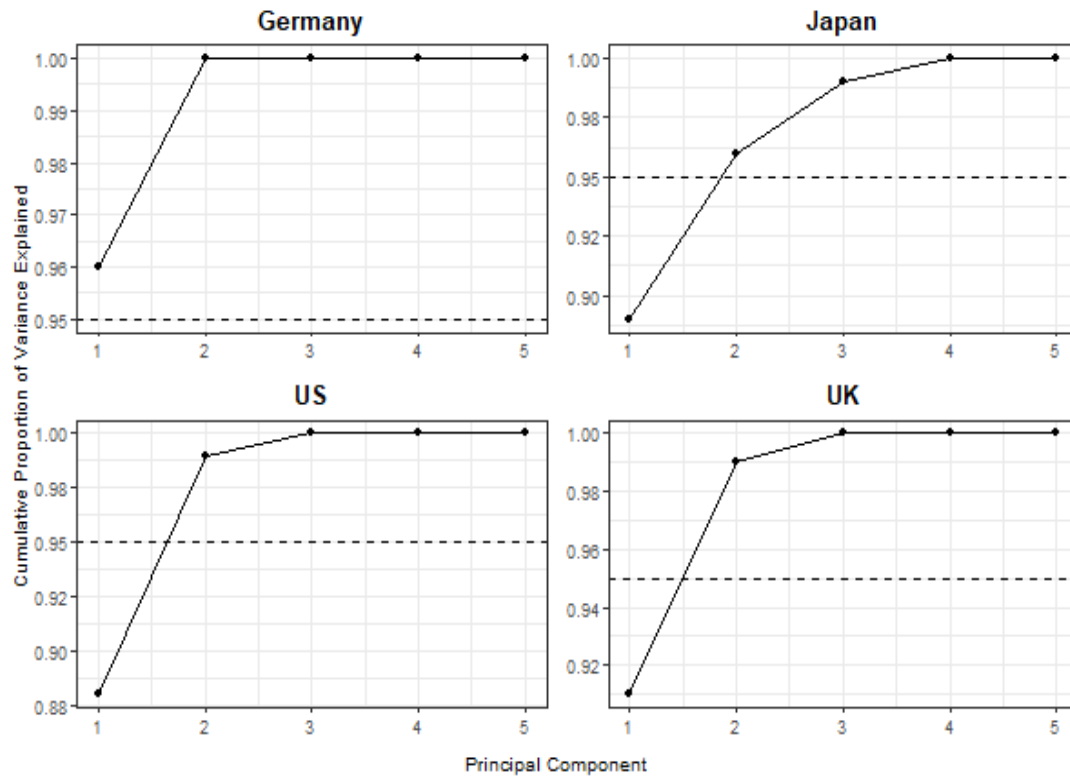


Figure 12: Cumulative proportion of explained variance of the first five principal components on daily yield data in the sample countries (sample period: 2000:01:04 - 2020:02:28). *Source: own figure based on own calculations.*

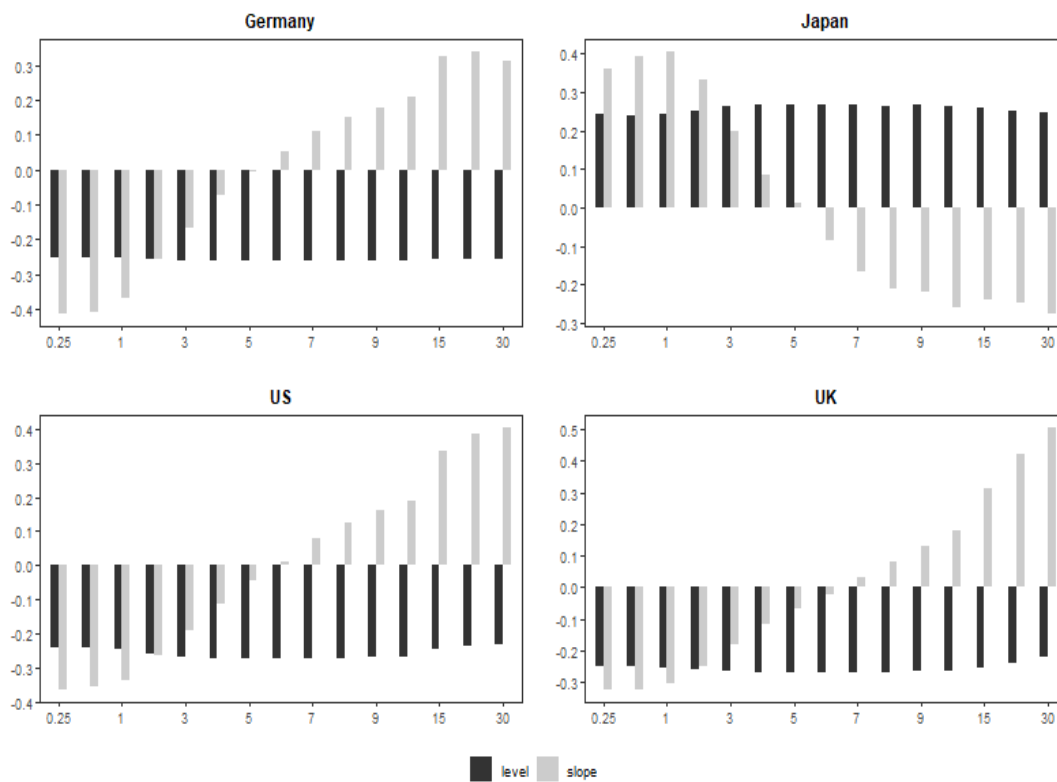


Figure 13: Principal component loadings. *Source: own figure based on own calculations.*

The resulting IRFs of inflation and industrial production following a financial and macroeconomic uncertainty shocks are plotted in *Figure 14* and *Figure 15* respectively. The model from which they are attained is defined the same way as equation (3) but with

$$y_t = [\text{uncertainty}, \text{industrial production}, \text{inflation}, L, S]'. \quad (5)$$

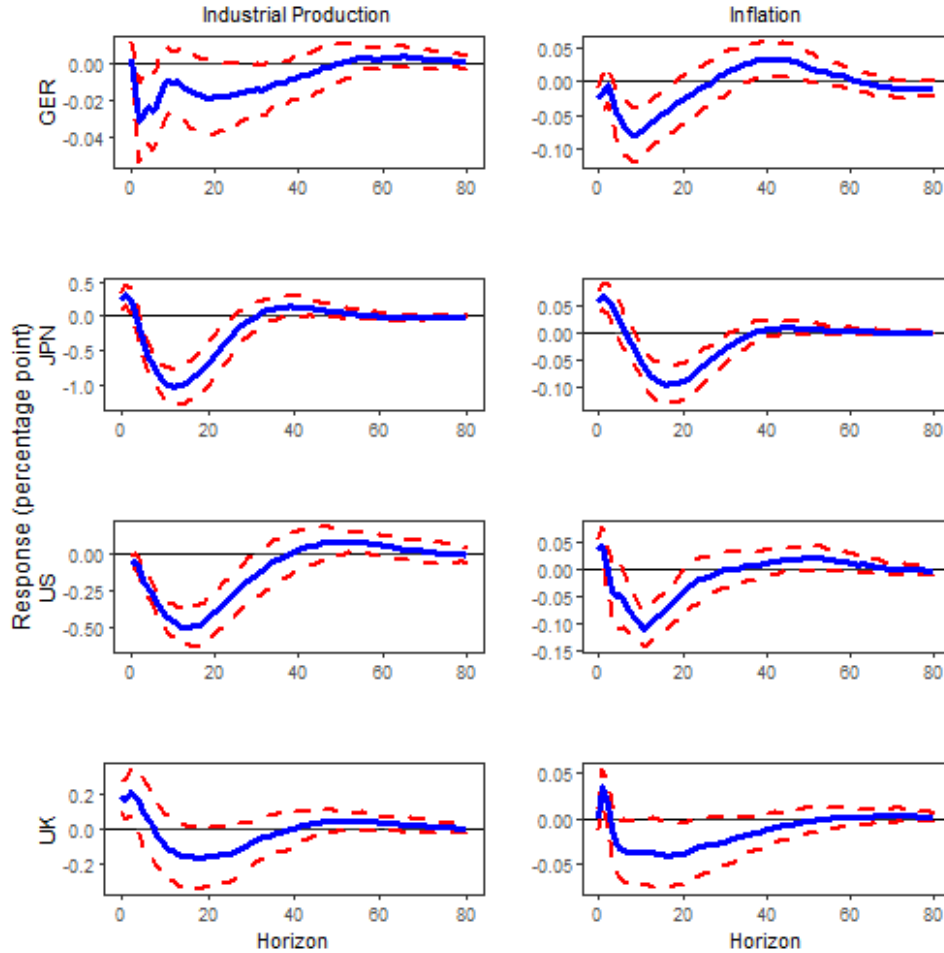


Figure 14: Impulse response (percentage point) of the macroeconomic series to a one-standard deviation shock of financial uncertainty as measured by Jurado, Ludvigson & Ng (2019). Point estimates identified by the solid blue lines, the red dashed lines indicate the 68% bootstrapped confidence bands. *Source: own figure based on own calculations.*

Industrial production declines immediately after a shock of financial uncertainty, than it recovers and seems to turn moderately positive in some cases, before converges back to steady state. The response patterns are fairly uniform across the countries for both uncertainty indices.

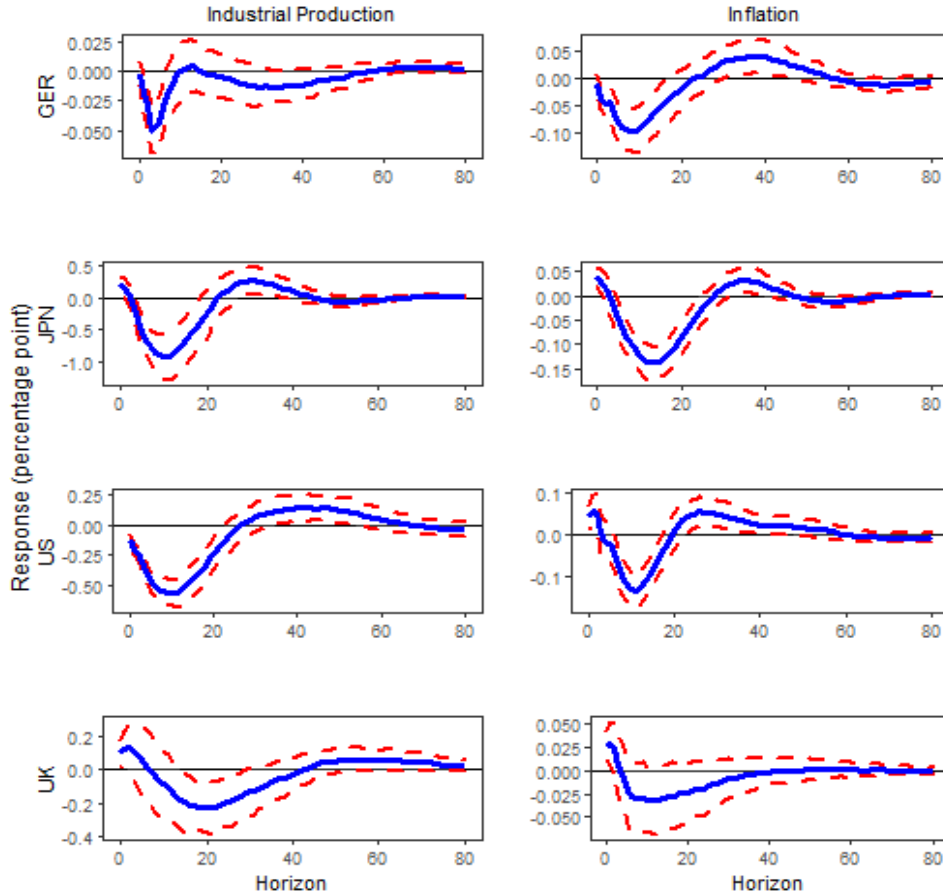


Figure 15: Impulse response (percentage point) of the macroeconomic series to a one-standard deviation shock of macroeconomic uncertainty as measured by Jurado, Ludvigson & Ng (2015). Point estimates identified by the solid blue lines, the dashed red line indicate the 68% bootstrapped confidence bands. *Source: own figure based on own calculations.*

The quick decrease of industrial production can explain the observed short-yield drops, as it usually triggers monetary policy easing. The peak negative responses at middle-horizon (20-30 months) can also explain the curvature factors' drop (as it drives the middle of the term structure), so why the curves get less humped. Since the various maturities are connected, the long rates will drop as well. The rebound of industrial production matches the observations in the literature (Caggiano et al. [2014], Castelnuovo [2019]), and is theoretically aided by Bloom [2009]. His model states that heightened uncertainty leads to the reallocation of resources from low to high-productive companies, which in turn leads to increased production in the future. Consequently, uncertainty induces sharp recessions with quick recoveries. If investors expect the observed recovery and eventual overshoot of industrial production, it can explain the drop of the long-end of the yield curves, and might leaves the short-end unaffected.

The reaction of inflation to uncertainty shocks is very similar to that of industrial production. The same sign of the macro variable responses categorizes uncertainty jumps as demand side shocks. The response differences of inflation to the two types of uncertainty shocks are

negligible. The empirical findings about the inflation's reaction varies in the literature. For example, Leduc and Liu [2016] report inflation drop. They construct a model with labor market search frictions, where firms stop posting vacancies due to a potential decrease in output, which entails lower expected values from hiring and in turn drives up unemployment. Hence, the decreased demand will squeeze the price level. Similarly, Basu and Bundick [2017] and Caggiano et al. [2014] find negative inflation response, with considerably higher negative peaks and higher explained variances by uncertainty, when responses are conditional on recessions. Again, the zero lower bound comes to play a role: they emphasize that linear VAR models most likely underestimate the effects of uncertainty. Contrary, Castelnuovo [2019] finds moderate inflation rise after uncertainty shocks. My observed negative jump in price levels further implies decreasing yields, most likely at every maturities. Although, it is not clear whether this response contributes to the steepening of the curves. If short-term expectations are affected more - which might be plausible from the mid-term recovery -, than short-rates drop more intensely. So as if investors are shortening their portfolios to insure against inflationary risk.

Table 8 to Table 11 (Appendix) show the variance decompositions at 1-,12- and 60-month horizons. It can be seen that the incorporation of macroeconomic variables considerably dwarfed the importance of uncertainty indices in explaining the factor movements. It is especially true in the case of financial uncertainty, where the explained shares at 60-month horizons do not exceed 10% (note that it is only *relatively* unimportant compared to the models without macro fundamentals). This seems to reinforce that a big share of yield movements following uncertainty shocks happen through macro fundamentals. Indeed, uncertainty is responsible for a huge proportion of variations in the macro variables, especially at longer horizons (easily exceeding 50-60% at 12 or 60 months) in most countries. These findings line up with those of Caggiano et al. [2014], Basu and Bundick [2017], Aastveit et al. [2017] and many others who show that the combined effects of uncertainty is what matters the most and its countercyclical nature.¹³

Diebold et al. [2006] find that the first two factor correspond to inflation and the cyclical behavior of the economy. According to my findings, the predictive power of inflation on level variations is weak at short horizons but gets considerably stronger later, although it widely varies across countries. There is an even weaker link between industrial production and slope. The factors are responsible for an even smaller variation in the macro series. This is in line with the findings of Diebold et al. [2006], that the effects from macro variables to yields are stronger, but likely a bidirectional relationship exists.

¹³For completeness, I show the impulse response of the factors to uncertainty shocks in Figure 16 and Figure 17, with $y_t = [\text{uncertainty}, \text{industrial production}, \text{inflation}, L, S]'$. There are no detectable changes compared to the uncertainty-factors only models.

6 Robustness of the results

I confirm the robustness of my baseline results by considering changes in data treatment and model specifications. Specifically, I test whether (i) using end of month yield data makes a difference in the factor responses after uncertainty shocks; (ii) averaging the factors from second half of month t until the middle of month $t + 1$. I consider the following variant of my baseline models: (iii) relaxing the exogeneity assumption on the uncertainty indices.

6.1 Different data treatments

As the use of end of month data is more common in the literature (e.g. Diebold and Li [2006]; Connolly et al. [2018]), it might be interesting to observe how sensitive my results are to this change. Also, as Connolly et al. [2018] emphasized, Jurado et al. [2015] use the revised version of the indices instead of real time estimates, so it might be more accurate to use their delayed values. Keeping this in mind, I test the impulse responses and average values from middle of month t to middle of month $t + 1$ when observing the effects of uncertainty shocks. The resulting impulse responses for financial and macroeconomic uncertainty are shown in *Figure 18* and *Figure 19* (Appendix) respectively. The differences in the responses are negligible and it is hard to conclude anything solidly regarding the differences. The average share of explained variances are shown in *Table 12* and *Table 13* for financial and macroeconomic uncertainty. Some quantitatively noteworthy changes can be observed in a few cases (in level and slope, and mainly between the baseline month t average and middle t to middle $t + 1$ averages), but the differences are mostly negligible.

6.2 Relaxing the exogeneity assumption

As the exogeneity assumption on uncertainty is ambiguous, it can be meaningful to see the extent to which this assumption empirically matters. I re-estimate my uncertainty with factors-only models, meaning that I allow the first two latent factors to contemporaneously influence uncertainty. The estimation is based on equation (3), with monthly averaged data but with y_t reads as follows:

$$y_t = [L, S, \text{uncertainty}, C]'. \quad (6)$$

The results are presented at *Table 14* and *Table 15*. As opposed to the robustness of the different data treatments, the exogeneity assumption seems to matter a lot (in terms of average share of explained variances). More precisely, when uncertainty is assumed to be endogenously determined by level and slope, there are large differences in the average explained shares from

these two factors.¹⁴ It seems that when exogeneity is relaxed for the financial uncertainty index, the explained variance shares are usually higher (with the exception of the US). However, for macroeconomic uncertainty, the result is the opposite. Ludvigson et al. [2021] states that "sharply higher macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while uncertainty about financial markets is a likely source of output fluctuations". In the case of yields, it seems that allowing for bidirectional contemporaneous effects enhances the predictive power of financial, while reduces for macroeconomic uncertainty.

7 Conclusion

In this paper, I argue that financial and macroeconomic uncertainty play a considerable role in explaining the term structure of interest rates in four developed countries, under the period 2000:01- 2020:02. I obtain the smooth yield curves with the parsimonious three-factor model of Diebold and Li [2006] and estimate VAR models to examine the dynamic interactions between the factors and uncertainty.

My main empirical findings are as follows. Increased uncertainty is associated with [1] significant negative yield responses and [2] more intense drops of the short-maturities (hence, the yield curves become temporarily steeper). Moreover, variance decompositions reveal that [3] uncertainty is responsible for a non-trivial share of yield variations (although, it widely varies across the countries). The rolling window analysis show that [4] substantial variations are present depending on the selected sample period, and the observed yield curve responses are likely connected to monetary policy reactions. It is suspected that the zero-lower bound influences the way how uncertainty affects the term structure, as it coincides with opposite directional curve rotations (the long-maturities tend to be more responsive). Incorporating inflation and industrial production to the models provides evidence that the [5] dynamic yield-uncertainty interactions happen through macroeconomic fundamentals, such as inflation and industrial production. The decrease in both of these variables - following uncertainty shocks - slightly supports both the role of investor expectations and the role of monetary policy actions behind the observed yield curve responses. My results remain robust to different data treatments, however, the relaxation of exogeneity largely influences the explained share of variances.

Finally, the preliminary Granger-causality estimations are weak evidence that uncertainty should be treated as either an exogenous, or a mixture of exogenous and endogenous source of variation in the yield movements.

This paper provides foundation for further research on uncertainty-yield relations. It would

¹⁴Cheng and Chiu [2018] examine this issue using Global Geopolitical Risk Index in 38 emerging countries, and find only small differences.

be interesting to see how these results hold on a bigger sample of countries. Also, other uncertainty metrics can be incorporated for comparison purposes. At last, possible nonlinearities in the effects should be accounted for. As many authors point out (e.g. Caggiano et al. [2014]; Shang [2022]), the impact of uncertainty is highly dependent on the stance of various other factors.

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Appendix

Table 5: Descriptive statistics, monthly averaged factors

	Mean	Std.dev.	Min	Max	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(30)$
Germany							
Level	3.51240	1.777581	-0.191077	6.353350	0.982065	0.807801	0.594793
Slope	-1.92401	1.082100	-4.501187	0.025157	0.966873	0.374593	-0.290888
Curvature	-3.63090	1.746954	-6.566384	0.492466	0.946824	0.364585	-0.002841
Japan							
Level	1.84507	0.837649	0.063428	3.045032	0.979458	0.740861	0.526645
Slope	-1.45349	0.679988	-2.776574	-0.147781	0.971453	0.685444	0.491414
Curvature	-3.84465	1.364278	-5.918482	-1.217310	0.968581	0.557750	0.226119
United States							
Level	4.51336	1.264350	1.907489	6.862066	0.967179	0.707275	0.518710
Slope	-2.60952	1.776985	-5.475907	0.766042	0.979069	0.454854	-0.274967
Curvature	-3.82863	2.730018	-9.465136	2.757245	0.967781	0.560026	0.017423
United Kingdom							
Level	3.88253	1.198715	0.983013	5.605067	0.978415	0.763906	0.508846
Slope	-1.56429	1.745532	-5.218105	1.450109	0.984935	0.639129	0.130618
Curvature	-2.06849	3.562012	-8.372086	7.717781	0.971895	0.707824	0.433059

Notes: The table presents descriptive statistics of the monthly averaged factors. The last three columns show the sample autocorrelations of 1, 12 and 30 months. The sample period is 2000:01-2020:02.

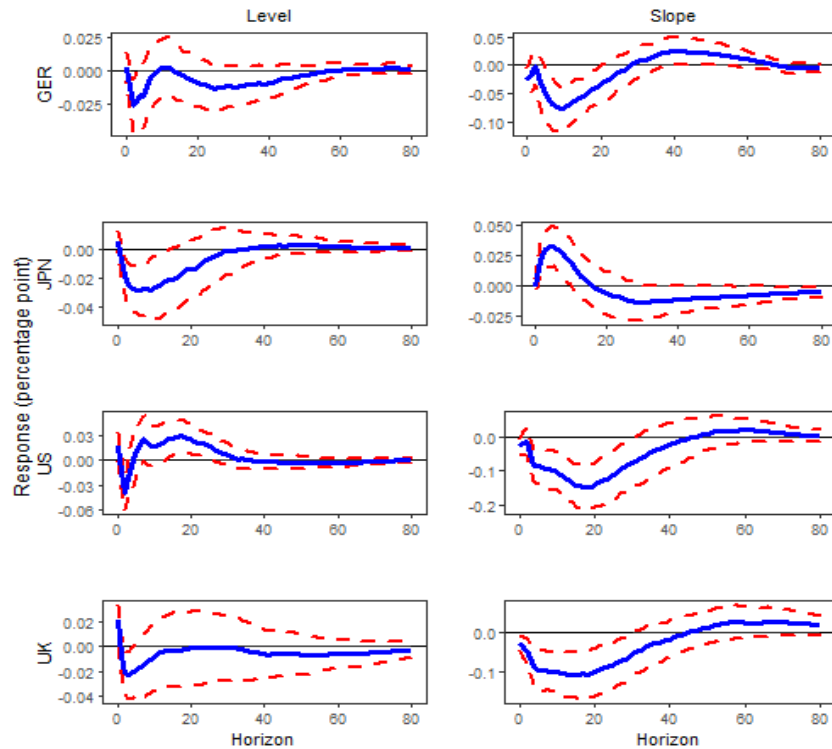


Figure 16: Impulse responses (percentage points) of the factors to a one-standard deviation shock of financial uncertainty(based of equation (3) with $y_t = [financial\ uncertainty, industrial\ production, inflation, L, S]'$).

Table 6: Forecast error variance decomposition table for financial uncertainty-yields model

Nelson-Siegel factors				
Horizon	JLN financial	Level	Slope	Curvature
GERMANY				
Variance Decomposition of Level				
1-month	0.00097	0.99902	0	0
3-month	0.00345	0.99014	0.00530	0.00109
6-month	0.01557	0.95542	0.02301	0.00598
1-year	0.02099	0.93619	0.03732	0.00547
3-years	0.04717	0.84231	0.03114	0.07936
5-years	0.05666	0.82461	0.03069	0.08802
Variance Decomposition of Slope				
1-month	0.01819	0.47321	0.50858	0
3-month	0.05474	0.50184	0.41071	0.03268
6-month	0.06286	0.42384	0.41230	0.10098
1-year	0.12261	0.38876	0.32268	0.16592
3-years	0.13335	0.46964	0.21957	0.17742
5-years	0.14689	0.43318	0.20379	0.21611
Variance Decomposition of Curvature				
1-month	0.00103	0.04360	0.09214	0.86321
3-month	0.00304	0.06065	0.07762	0.85867
6-month	0.01735	0.09035	0.07165	0.82062
1-year	0.03105	0.14617	0.05820	0.76456
3-years	0.03132	0.23346	0.04994	0.68526
5-years	0.03587	0.23243	0.04953	0.68215
JAPAN				
Variance Decomposition of Level				
1-month	0.00135	0.99864	0	0
3-month	0.00082	0.99478	0.00163	0.00275
6-month	0.00590	0.98455	0.00426	0.00527
1-year	0.02266	0.96243	0.00769	0.00720
3-years	0.06521	0.91740	0.01045	0.00692
5-years	0.06860	0.91250	0.01033	0.00855
Variance Decomposition of Slope				
1-month	0.00197	0.81585	0.18217	0
3-month	0.00173	0.78143	0.21672	0.00011
6-month	0.00858	0.76302	0.22615	0.00223
1-year	0.01893	0.74686	0.21766	0.01654
3-years	0.02877	0.65805	0.16976	0.14340
5-years	0.08720	0.55790	0.13802	0.21686
Variance Decomposition of Curvature				
1-month	0.00700	0.28746	0.33465	0.37087
3-month	0.00449	0.36733	0.32325	0.30491
6-month	0.00264	0.42973	0.29223	0.27538
1-year	0.00373	0.49686	0.24304	0.25636
3-years	0.02501	0.56371	0.16991	0.24134
5-years	0.041005	0.55362	0.15591	0.24945

Nelson-Siegel factors				
Horizon	JLN financial	Level	Slope	Curvature
UNITED STATES				
Variance Decomposition of Level				
1-month	0.00540	0.99459	0	0
3-month	0.01270	0.97512	0.00120	0.01096
6-month	0.020815	0.95103	0.00277	0.02537
1-year	0.02155	0.93022	0.00313	0.04508
3-years	0.05481	0.89241	0.00356	0.04920
5-years	0.05632	0.88943	0.00360	0.05063
Variance Decomposition of Slope				
1-month	0.00166	0.70668	0.29164	0
3-month	0.00748	0.58520	0.34195	0.06535
6-month	0.01504	0.40381	0.38286	0.19827
1-year	0.11481	0.22386	0.31188	0.34943
3-years	0.33174	0.19059	0.15765	0.32000
5-years	0.33518	0.21160	0.14827	0.30492
Variance Decomposition of Curvature				
1-month	0.00095	0.00060	0.05031	0.94812
3-month	0.01963	0.00030	0.06649	0.91356
6-month	0.03290	0.00349	0.09542	0.86817
1-year	0.07527	0.02239	0.10144	0.80088
3-years	0.23027	0.12546	0.06206	0.58219
5-years	0.24136	0.14891	0.05859	0.55111
UNITED KINGDOM				
Variance Decomposition of Level				
1-month	0.00750	0.99249	0	0
3-month	0.01825	0.97827	0.00245	0.00100
6-month	0.01206	0.97878	0.00826	0.00088
1-year	0.00824	0.98370	0.00696	0.00108
3-years	0.00672	0.96528	0.01041	0.01757
5-years	0.01548	0.92385	0.01348	0.04717
Variance Decomposition of Slope				
1-month	0.00927	0.44372	0.54699	0
3-month	0.03201	0.37003	0.58060	0.01734
6-month	0.09034	0.33015	0.52638	0.05312
1-year	0.26961	0.31267	0.31819	0.09951
3-years	0.37128	0.41474	0.13786	0.07610
5-years	0.32766	0.46980	0.12211	0.08041
Variance Decomposition of Curvature				
1-month	0.00512	0.06102	0.13138	0.80246
3-month	0.00737	0.02284	0.07926	0.89051
6-month	0.06164	0.01773	0.04849	0.87212
1-year	0.15648	0.04143	0.02788	0.77419
3-years	0.25764	0.18380	0.01418	0.54437
5-years	0.24755	0.27200	0.01356	0.46687

Notes: The table presents the forecast error variance decompositions based on the model defined by Equation (3), with $y_t = [\text{macro uncertainty}, L, S, C]'$.

Table 7: Forecast error variance decomposition table for macroeconomic uncertainty - yields model

Nelson-Siegel factors				
Horizon	JLN Macro	Level	Slope	Curvature
GERMANY				
Variance Decomposition of Level				
1-month	0.009228	0.99077	0	0
3-month	0.006500	0.98426	0.00808	0.00114
6-month	0.031387	0.95137	0.013896	0.00334
1-year	0.033866	0.94738	0.01583	0.00291
3-years	0.050113	0.73614	0.08054	0.13319
5-years	0.077806	0.678810	0.07923	0.16415
Variance Decomposition of Slope				
1-month	0.02446	0.49721	0.478319	0
3-month	0.06291	0.54112	0.36118	0.03476
6-month	0.11311	0.45602	0.29993	0.13092
1-year	0.26133	0.358582	0.16956	0.21052
3-years	0.29138	0.35547	0.16316	0.18996
5-years	0.29499	0.32801	0.15776	0.21923
Variance Decomposition of Curvature				
1-month	0.014840	0.035092	0.07035	0.87971
3-month	0.02060	0.058116	0.034041	0.88723
6-month	0.01489	0.09814	0.019547	0.86740
1-year	0.011611	0.16871	0.02262	0.79704
3-years	0.013088	0.24608	0.03582	0.70500
5-years	0.01569	0.24390	0.03978	0.70061
JAPAN				
Variance Decomposition of Level				
1-month	0.00012	0.99987	0	0
3-month	0.00125	0.99272	0.00064	0.00538
6-month	0.00198	0.98727	0.00167	0.00906
1-year	0.00376	0.98053	0.00288	0.01280
3-years	0.05107	0.90290	0.01487	0.03114
5-years	0.05266	0.89012	0.020177	0.03704
Variance Decomposition of Slope				
1-month	0.00058	0.81926	0.180155	0
3-month	0.002181	0.79820	0.19908	0.00053
6-month	0.00190	0.79518	0.20151	0.00139
1-year	0.03789	0.76699	0.18216	0.01294
3-years	0.30330	0.51915	0.122238	0.05530
5-years	0.33061	0.45149	0.10721	0.11067
Variance Decomposition of Curvature				
1-month	0.00036	0.27187	0.35054	0.37720
3-month	0.00020	0.34070	0.34473	0.31434
6-month	0.00027	0.39028	0.32224	0.28719
1-year	0.00681	0.43643	0.28609	0.27065
3-years	0.08846	0.45328	0.21409	0.24415
5-years	0.12086	0.43075	0.19897	0.24940

Nelson-Siegel factors				
Horizon	JLN Macro	Level	Slope	Curvature
UNITED STATES				
Variance Decomposition of Level				
1-month	0.01897	0.98102	0	0
3-month	0.03928	0.95579	0.00133	0.00364
6-month	0.04518	0.91874	0.009663	0.02641
1-year	0.06044	0.85480	0.01144	0.07329
3-years	0.17662	0.73674	0.01927	0.06736
5-years	0.17516	0.72368	0.0257	0.07537
Variance Decomposition of Slope				
1-month	0.02742	0.68797	0.28459	0
3-month	0.06841	0.51603	0.35858	0.05696
6-month	0.06020	0.31459	0.40394	0.22121
1-year	0.12287	0.15478	0.31778	0.40456
3-years	0.313515	0.08696	0.17662	0.42289
5-years	0.322986	0.08559	0.182347	0.40907
Variance Decomposition of Curvature				
1-month	0.008164	4.735e-05	0.039033	0.9527
3-month	0.018488	9.921e-05	0.04696	0.93445
6-month	0.014277	0.002884	0.054912	0.92792
1-year	0.023758	0.01810	0.053463	0.90466
3-years	0.158884	0.031654	0.042340	0.76712
5-years	0.179638	0.03238	0.051974	0.73600
UNITED KINGDOM				
Variance Decomposition of Level				
1-month	0.010581	0.98941	0	0
3-month	0.021464	0.97270	0.004084	0.00174
6-month	0.013947	0.97913	0.005620	0.00129
1-year	0.016003	0.97579	0.00539	0.00282
3-years	0.043191	0.87072	0.081423	0.00465
5-years	0.095792	0.77706	0.100121	0.02702
Variance Decomposition of Slope				
1-month	0.006941	0.474541	0.51851	0
3-month	0.0598610	0.39602	0.529379	0.01473
6-month	0.244162	0.28723	0.42861	0.03999
1-year	0.551401	0.17034	0.21688	0.06137
3-years	0.609632	0.161780	0.142221	0.08636
5-years	0.55741	0.204839	0.15737	0.08036
Variance Decomposition of Curvature				
1-month	0.003137	0.045320	0.117679	0.83386
3-month	0.022508	0.014193	0.053040	0.91025
6-month	0.049088	0.010040	0.0281346	0.91273
1-year	0.11599	0.0230038	0.016923	0.84407
3-years	0.253245	0.0968402	0.013608	0.63630
5-years	0.24969	0.147927	0.032885	0.56949

Notes: The table presents the forecast error variance decompositions based on the model defined by Equation (3), with $y_t = [financial\ uncertainty, L, S, C]^t$.

Table 8: Forecast error variance decomposition table for financial uncertainty-macro variables-yields model in Germany and Japan

Horizon	JLN financial	Macro Variables		Nelson-Siegel factors	
		Inflation	Industrial Production	Level	Slope
GERMANY					
Variance Decomposition of Level					
1-month	0.00247	0.03036	0.01196	0.95521	0.00000
12-months	0.01628	0.07459	0.00430	0.89365	0.01118
60-months	0.02160	0.06944	0.00356	0.88073	0.02467
Variance Decomposition of Slope					
1-month	0.00292	0.00268	0.00129	0.07604	0.91707
12-months	0.03202	0.00801	0.00132	0.14724	0.81141
60-months	0.02925	0.02501	0.00150	0.29804	0.64620
Variance Decomposition of Inflation					
1-month	0.00700	0.99300	0.00000	0.00000	0.00000
12-months	0.06305	0.87062	0.04298	0.01252	0.01083
60-months	0.18639	0.64537	0.05280	0.03325	0.08219
Variance Decomposition of Industrial Production					
1-month	0.00347	0.01322	0.98331	0.00000	0.00000
12-months	0.27007	0.03660	0.65600	0.01873	0.01860
60-months	0.34729	0.12807	0.35518	0.04655	0.12291
JAPAN					
Variance Decomposition of Level					
1-month	0.00951	0.00167	0.00027	0.98854	0.00000
12-months	0.04131	0.00303	0.01361	0.92263	0.01942
60-months	0.07416	0.00396	0.02290	0.85714	0.04185
Variance Decomposition of Slope					
1-month	0.00215	0.00467	0.00464	0.26634	0.72220
12-months	0.00282	0.00266	0.05621	0.44561	0.49270
60-months	0.02762	0.00428	0.06527	0.55373	0.34910
Variance Decomposition of Inflation					
1-month	0.03555	0.96445	0.00000	0.00000	0.00000
12-months	0.04494	0.87694	0.07454	0.00008	0.00350
60-months	0.29185	0.61630	0.06508	0.01273	0.01403
Variance Decomposition of Industrial Production					
1-month	0.01028	0.00153	0.98819	0.00000	0.00000
12-months	0.24773	0.05401	0.60218	0.00134	0.09474
60-months	0.48940	0.04943	0.33165	0.04362	0.08591

Notes: The table presents the forecast error variance decompositions based on the model defined by Equation (3), with $y_t = [\text{financial uncertainty, industrial production, inflation, } L, S]'$.

Table 9: Forecast error variance decomposition table for financial uncertainty-macro variables-yields model in US and UK

Horizon	JLN financial	Macro Variables		Nelson-Siegel factors	
		Inflation	Industrial Production	Level	Slope
UNITED STATES					
Variance Decomposition of Level					
1-month	0.02249	0.04298	0.00206	0.93248	0.00000
12-months	0.02497	0.08763	0.05906	0.82355	0.00479
60-months	0.05555	0.10514	0.05805	0.77043	0.01083
Variance Decomposition of Slope					
1-month	0.00039	0.00023	0.00029	0.00535	0.99374
12-months	0.09047	0.00467	0.00125	0.02125	0.88235
60-months	0.16739	0.01905	0.00120	0.21975	0.59261
Variance Decomposition of Inflation					
1-month	0.02715	0.97285	0.00000	0.00000	0.00000
12-months	0.08892	0.81187	0.09172	0.00580	0.00168
60-months	0.15445	0.69134	0.07840	0.06753	0.00828
Variance Decomposition of Industrial Production					
1-month	0.01997	0.00037	0.97967	0.00000	0.00000
12-months	0.50120	0.01498	0.45321	0.02203	0.00858
60-months	0.49654	0.05132	0.14722	0.28184	0.02308
UNITED KINGDOM					
Variance Decomposition of Level					
1-month	0.03157	0.00098	0.00000	0.96745	0.00000
12-months	0.01422	0.01721	0.00167	0.96086	0.00605
60-months	0.02325	0.11346	0.00210	0.85198	0.00921
Variance Decomposition of Slope					
1-month	0.00542	0.01888	0.00119	0.07095	0.90355
12-months	0.05027	0.01428	0.22521	0.12970	0.58054
60-months	0.07341	0.13583	0.15249	0.40331	0.23496
Variance Decomposition of Inflation					
1-month	0.00574	0.99426	0.00000	0.00000	0.00000
12-months	0.01556	0.95828	0.00273	0.01648	0.00695
60-months	0.02300	0.89965	0.00636	0.03939	0.03160
Variance Decomposition of Industrial Production					
1-month	0.00996	0.00028	0.98976	0.00000	0.00000
12-months	0.01355	0.00140	0.89930	0.03870	0.04705
60-months	0.05827	0.08852	0.55436	0.25908	0.03976

Notes: The table presents the forecast error variance decompositions based on the model defined by Equation (3), with $y_t = [\text{financial uncertainty, industrial production, inflation, } L, S]'$.

Table 10: Forecast error variance decomposition table for macroeconomic uncertainty-macro variables-yields model in Germany and Japan

Horizon	JLN macro	Macro Variables		Nelson-Siegel factors	
		Inflation	Industrial Production	Level	Slope
GERMANY					
Variance Decomposition of Level					
1-month	0.02582	0.02776	0.00445	0.94197	0.00000
12-months	0.03233	0.08352	0.03573	0.84679	0.00162
60-months	0.04145	0.07490	0.14446	0.68327	0.05592
Variance Decomposition of Slope					
1-month	0.01734	0.00756	0.00855	0.06567	0.90087
12-months	0.01855	0.00406	0.01027	0.13546	0.83166
60-months	0.02237	0.00717	0.04207	0.25583	0.67256
Variance Decomposition of Inflation					
1-month	0.01748	0.98252	0.00000	0.00000	0.00000
12-months	0.15486	0.72152	0.08742	0.01299	0.02320
60-months	0.31335	0.49249	0.13915	0.02363	0.03137
Variance Decomposition of Industrial Production					
1-month	0.01000	0.00679	0.98321	0.00000	0.00000
12-months	0.30373	0.02812	0.58040	0.02231	0.06543
60-months	0.40109	0.15632	0.35984	0.02517	0.05758
JAPAN					
Variance Decomposition of Level					
1-month	0.00543	0.00037	0.00142	0.99278	0.00000
12-months	0.00550	0.00158	0.01011	0.97913	0.00367
60-months	0.03048	0.00771	0.06690	0.81609	0.07881
Variance Decomposition of Slope					
1-month	0.00946	0.00358	0.00753	0.26674	0.71269
12-months	0.01173	0.00323	0.05498	0.43179	0.49828
60-months	0.10316	0.01784	0.05680	0.44777	0.37443
Variance Decomposition of Inflation					
1-month	0.01631	0.98369	0.00000	0.00000	0.00000
12-months	0.19069	0.74890	0.04066	0.01753	0.00222
60-months	0.45810	0.47425	0.03258	0.02937	0.00570
Variance Decomposition of Industrial Production					
1-month	0.00920	0.00545	0.98535	0.00000	0.00000
12-months	0.31448	0.06991	0.45760	0.02280	0.13522
60-months	0.42473	0.11894	0.31497	0.02081	0.12054

Notes: The table presents the forecast error variance decompositions based on the model defined by Equation (3), with $y_t = [\text{macro uncertainty, industrial production, inflation, } L, S]^t$.

Table 11: Forecast error variance decomposition table for macroeconomic uncertainty-macro variables-yields model in the US and UK

Horizon	JLN macro	Macro Variables		Nelson-Siegel factors	
		Inflation	Industrial Production	Level	Slope
UNITED STATES					
Variance Decomposition of Level					
1-month	0.02856	0.05671	0.00642	0.90831	0.00000
12-months	0.03574	0.09499	0.03938	0.80490	0.02499
60-months	0.13857	0.10138	0.06851	0.65878	0.03277
Variance Decomposition of Slope					
1-month	0.00837	0.00036	0.00020	0.00003	0.99103
12-months	0.03079	0.00771	0.01190	0.00491	0.94469
60-months	0.13913	0.01892	0.03871	0.02319	0.78005
Variance Decomposition of Inflation					
1-month	0.02572	0.97428	0.00000	0.00000	0.00000
12-months	0.11983	0.74398	0.10059	0.01505	0.02055
60-months	0.22286	0.61644	0.11518	0.02605	0.01946
Variance Decomposition of Industrial Production					
1-month	0.04609	0.00004	0.95387	0.00000	0.00000
12-months	0.58034	0.01504	0.33220	0.04999	0.02243
60-months	0.64936	0.07304	0.21004	0.04870	0.01887
UNITED KINGDOM					
Variance Decomposition of Level					
1-month	0.03052	0.00196	0.00019	0.96734	0.00000
12-months	0.02967	0.02339	0.00208	0.92953	0.01533
60-months	0.17966	0.11083	0.00916	0.68958	0.01078
Variance Decomposition of Slope					
1-month	0.01279	0.02189	0.00078	0.06129	0.90325
12-months	0.01829	0.01141	0.22419	0.11201	0.63410
60-months	0.11688	0.11767	0.23558	0.25830	0.27157
Variance Decomposition of Inflation					
1-month	0.04510	0.95490	0.00000	0.00000	0.00000
12-months	0.03004	0.91351	0.00115	0.04994	0.00536
60-months	0.02566	0.87522	0.00707	0.06037	0.03168
Variance Decomposition of Industrial Production					
1-month	0.00302	0.00030	0.99668	0.00000	0.00000
12-months	0.01295	0.00166	0.91512	0.04879	0.02148
60-months	0.07577	0.08466	0.62212	0.18508	0.03237

Notes: The table presents the forecast error variance decompositions based on the model defined by Equation (3), with $y_t = [\text{macro uncertainty, industrial production, inflation, } L, S]^t$.

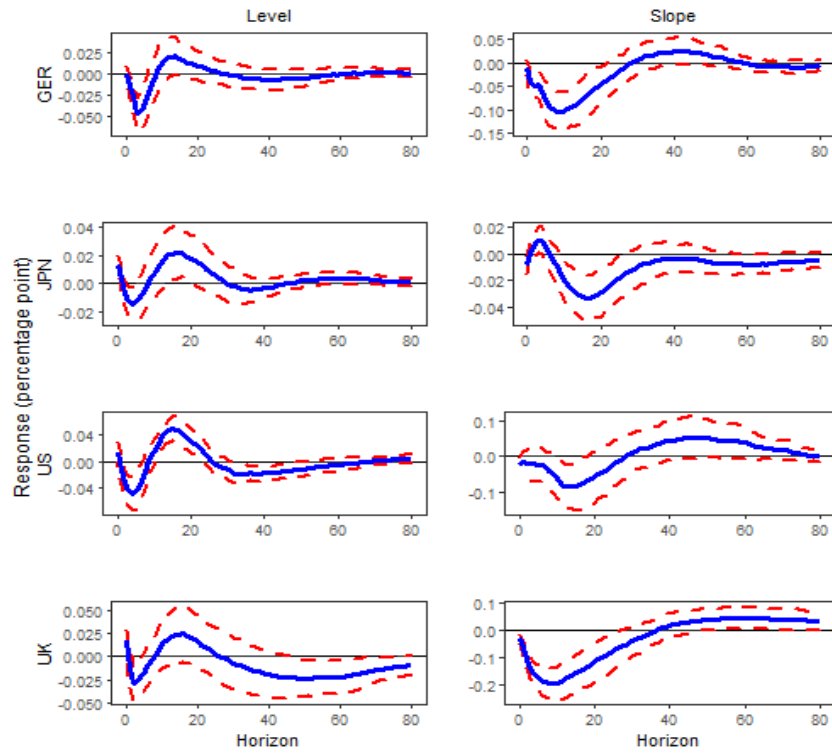


Figure 17: Impulse responses (percentage points) of the factors to a one-standard deviation shock of financial uncertainty(based of equation (3) with $y_t = [\text{macro uncertainty, industrial production, inflation, } L, S]'$).

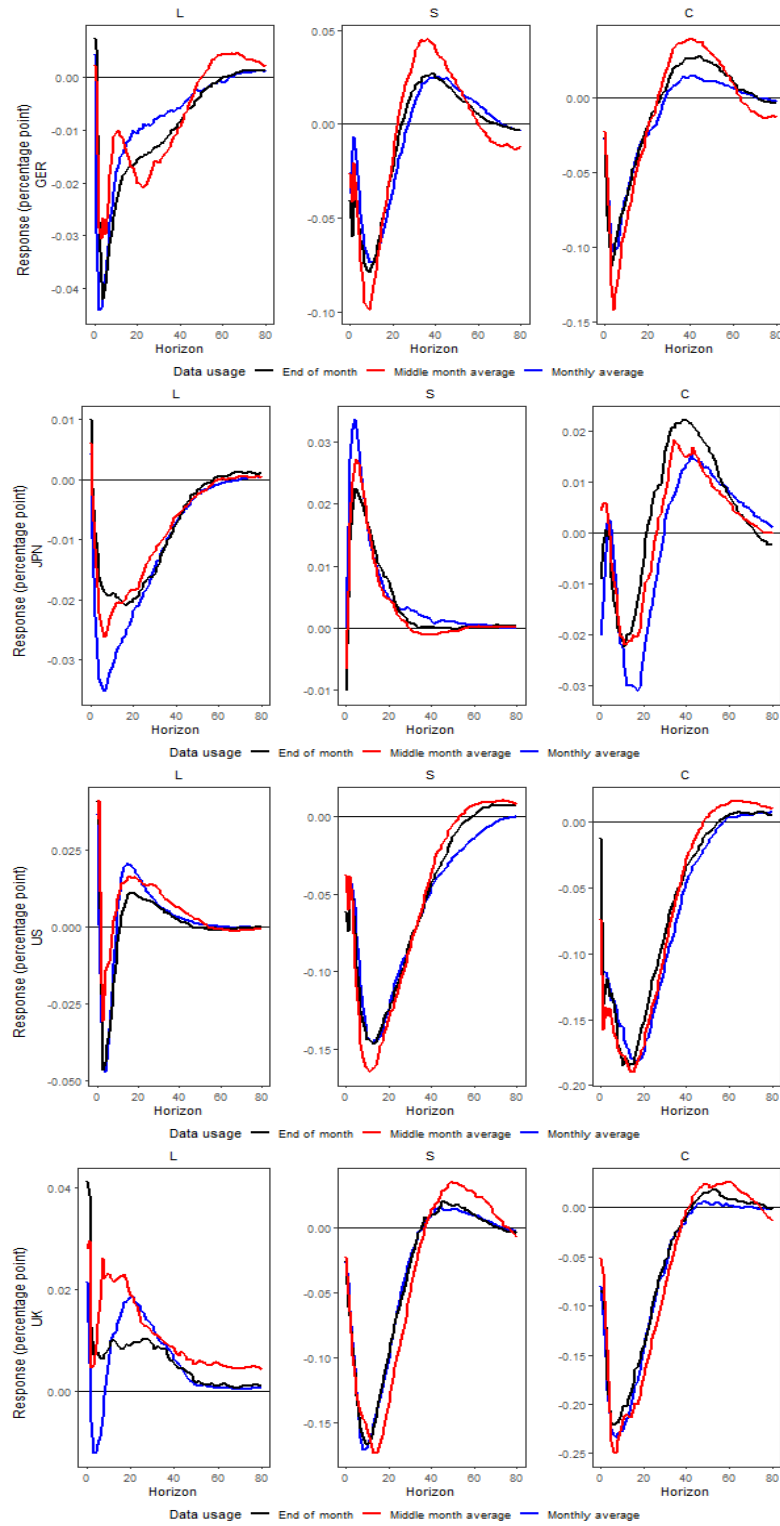


Figure 18: Impulse responses (point estimates) with data treatment variations, financial uncertainty shocks. The blue line indicates the same estimates as in Figure 6.

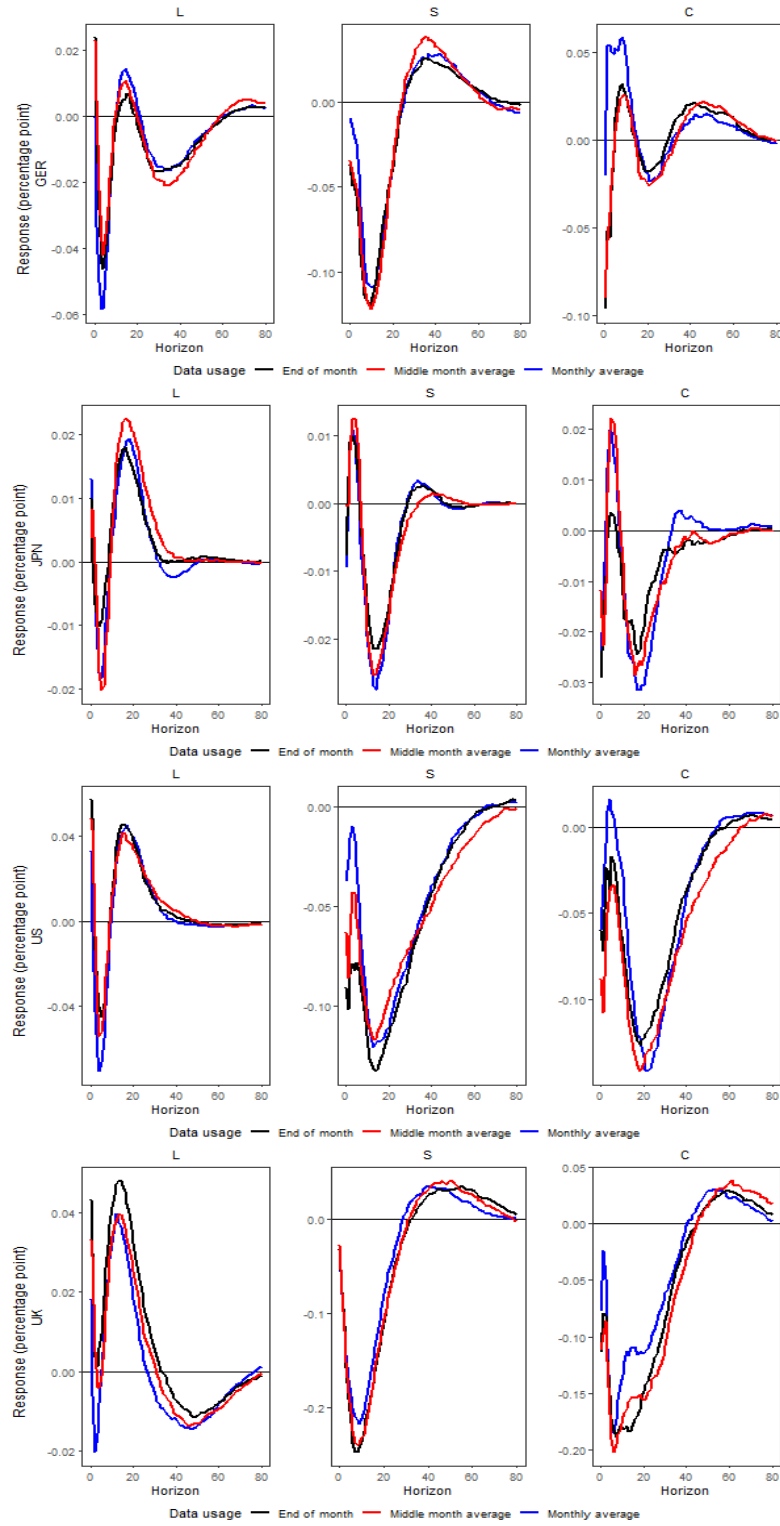


Figure 19: Impulse responses (point estimates) with data treatment variations, macroeconomic uncertainty shocks. The blue line indicates the same estimates as in Figure 7.

Table 12: Average share of variance (%) explained by financial uncertainty with different data treatment methods, h = 1-60

Country	Baseline (month t average)			End of month			Average from middle t to middle t+1		
	L	S	C	L	S	C	L	S	C
Germany	0.03741	0.12785	0.02951	0.05060	0.08801	0.03072	0.03115	0.10385	0.03215
Japan	0.04899	0.03356	0.02016	0.05214	0.04450	0.02530	0.03929	0.05019	0.03466
US	0.04286	0.24961	0.17261	0.05110	0.29966	0.17853	0.04441	0.32825	0.22685
UK	0.00943	0.30900	0.20725	0.01142	0.32683	0.25726	0.01607	0.39988	0.33450

Notes: The table presents the average explained variances (%) of the DL factors by financial uncertainty at the first 60 month horizon.

Table 13: Average share of variance (%) explained by macroeconomic uncertainty with different data treatment methods, h = 1-60

Country	Baseline (month t average)			End of month			Average from middle t to middle t+1		
	L	S	C	L	S	C	L	S	C
Germany	0.04687	0.26673	0.01384	0.05052	0.22338	0.01332	0.04359	0.24331	0.01126
Japan	0.03485	0.21552	0.06403	0.05349	0.26854	0.09865	0.05392	0.24314	0.08738
US	0.13431	0.24633	0.11214	0.13111	0.30753	0.11242	0.13005	0.29384	0.12278
UK	0.04582	0.53736	0.19433	0.05089	0.51737	0.21312	0.04361	0.49822	0.19844

Notes: The table presents the average explained variances (%) of the DL factors by macroeconomic uncertainty at the first 60 month horizon.

Table 14: Average share of variance (%) explained by financial uncertainty, base-case and no exogeneity assumed (h = 1-60)

Country	Base-case			No exogeneity		
	L	S	C	L	S	C
Germany	0.03741	0.12785	0.02951	0.06423	0.19862	0.01783
Japan	0.04899	0.03356	0.02016	0.03736	0.22213	0.06397
US	0.04286	0.24961	0.17261	0.14726	0.19696	0.10586
UK	0.00943	0.30900	0.20725	0.03615	0.48388	0.17022

Notes: The table presents the average explained variances (%) of the DL factors by financial uncertainty at the first 60 month horizon.

Base-case model $y_t = [financial\ uncertainty, L, S, C]'$; no exogeneity model $y_t = [L, S, financial\ uncertainty, C]'$.

Table 15: Average share of variance (%) explained by macroeconomic uncertainty, base-case and no exogeneity assumed (h = 1-60)

Country	Base-case			No exogeneity		
	L	S	C	L	S	C
Germany	0.04687	0.26673	0.01384	0.05059	0.07806	0.03361
Japan	0.03485	0.21552	0.06403	0.06236	0.04094	0.01686
US	0.13431	0.24633	0.11214	0.04705	0.23604	0.14941
UK	0.04582	0.53736	0.19433	0.01213	0.24500	0.18104

Notes: The table presents the average explained variances (%) of the DL factors by macroeconomic uncertainty at the first 60 month horizon. Base-case model $y_t = [macroeconomic\ uncertainty, L, S, C]'$; no exogeneity model $y_t = [L, S, macroeconomic\ uncertainty, C]'$.