Journal of International Money and Finance 108 (2020) 102152

Contents lists available at ScienceDirect

Journal of International Money and Finance

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

Credit intermediation and the transmission of macro-financial uncertainty: International evidence ☆

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A R T I C L E I N F O

Article history:
Available online 14 February 2020

JEL classification:
D80
E32
E44
G21

Keywords:
Uncertainty
Credit intermediation
Local projection method
State dependency

A B S T R A C T

This paper introduces a novel measure of global macro-financial uncertainty and examines the state-dependent transmission of uncertainty to economic activity. We show that global uncertainty shocks have adverse and nonlinear macroeconomic effects, with the nonlinearity being driven by different levels of country-specific banking sector distress. Both macroeconomic and financial market uncertainty are associated with lower economic activity, with the latter exerting stronger effects. The state dependency of the effect is prevalent in both cases. Our findings have important policy implications, highlighting both the state of the banking sector as well as the origin of uncertainty as crucial factors in the transmission of uncertainty.

1. Introduction

The adverse effects of uncertainty have traditionally been linked to real frictions that make agents reluctant to make consumption, investment and hiring decisions that are costly to reverse or even irreversible (Bloom, 2009; Bloom et al., 2018). In addition, uncertainty may also lead to an increase in precautionary savings, and thus, a reduction in consumption (Basu and Bundick, 2017; Fernández-Villaverde et al., 2015). A recent strand of the literature argues that uncertainty primarily works through financial frictions. Higher uncertainty increases the premium on external finance as banks and investors take into account the corresponding risk (Gilchrist et al., 2014; Caldara et al., 2016). In this paper, we evaluate the role of financial factors in the propagation of uncertainty by taking into account both the origin of uncertainty as well as the environment in which uncertainty shocks occur.

Alessandri and Mumtaz (2019) show that uncertainty shocks have recessionary effects at all times, but their impact on output is much larger when they coincide with a financial crisis. In this context, we shed light on the role of two important confounding factors, namely, the environment in the respective country on the one hand and the origin of the uncertainty

☆ We are grateful to two anonymous referees as well as seminar participants at the NOeG Annual Meeting 2019, the Economic Policy Seminar Alpenrhein, the research seminar at ifo Center Macroeconomics and Surveys, and the Annual International Conference on Macroeconomic Analysis and International Finance 2019 for very helpful comments.

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https://doi.org/10.1016/j.jimonfin.2020.102152

shock on the other. Referring to the first factor, we put a particular focus on credit intermediation and examine nonlinearities in the transmission of uncertainty shocks associated with the state of the banking sector. More precisely, we study the reaction of real economic activity to uncertainty in an environment in which credit intermediation is well functioning and in an environment in which it is distressed. Our second contribution is to examine whether the effects of uncertainty vary depending on its origin. Ludvigson et al. (2019) find that while uncertainty associated with macroeconomic developments is mainly an endogenous reaction to business cycle shocks, financial market uncertainty causes business cycle fluctuations. The measure of uncertainty that we propose in this paper allows us to distinguish whether uncertainty is driven by macroeconomic or financial market developments.

To distinguish between different states of the functioning of credit intermediation, we use an index by Romer and Romer (2017) that captures banking sector distress based on narrative accounts documented in the OECD Economic Outlook reports. The index identifies periods in which credit intermediation is disturbed. In our analysis, we make use of the fact that the index is constructed at the country level focusing on the state of the *domestic* banking sector, whereas our measure of uncertainty is constructed at the *global* level and explicitly focuses on uncertainty over future macroeconomic and financial market outcomes. As a consequence, our empirical strategy permits a separation of the corresponding effects of uncertainty and banking sector distress and allows us to study the interaction of the two.

Our measure of uncertainty is a mechanically constructed index based on Hotelling's (1931) *T*-squared statistic. This statistic is an effective and flexible tool to identify unusual developments in any set of variables at an aggregate level without imposing strong modeling assumptions. It captures deviations from historical mean and correlation patterns. We apply the statistic to a number of macroeconomic and financial market variables covering the G7 economies, which allows us to trace macro-financial uncertainty at the global level. While most of the literature focuses on some form of country-specific uncertainty, the global nature of our measure is key to our identification strategy. In addition, the construction of the measure allows us to quantify the contribution of individual input factors to the overall level of uncertainty at any point in time. We exploit this feature to evaluate the role of the origin of uncertainty in its transmission to economic activity.[1]

To evaluate the effects of uncertainty on economic activity, we estimate dynamic responses of GDP growth allowing for potential nonlinearities associated with the state of the banking sector in the Jordà (2005) local projection framework. Our empirical exercise reveals that an increase in global macro-financial uncertainty has particularly severe effects on GDP growth in cases in which the banking sector is already distressed, when the impact is approximately three times larger than that when credit intermediation is well functioning. This nonlinearity in the responses of economic activity is prevalent in the case of macroeconomic as well as financial uncertainty. However, the adverse effects of financial uncertainty are stronger relative to those of macroeconomic uncertainty. Moreover, a closer look at individual countries shows that in the vast majority of OECD countries, the impact of macro-financial uncertainty crucially depends on the resilience of the domestic banking sector.

The paper is structured as follows. Section 2 introduces our new measure for global macro-financial uncertainty. Section 3 lays out the empirical strategy we use to evaluate the effects of macro-financial uncertainty. In Section 4, we discuss our main results. Section 5 presents robustness checks and some additional analyses evaluating other measures of uncertainty. Section 6 concludes and discusses the main policy implications of our findings.

2. A new measure of macro-financial uncertainty

The literature proposes a wide range of uncertainty proxies (see the surveys by Bloom (2014) and Castelnuovo (2019) for an overview). A nonexhaustive list includes the implied and realized volatilities of the S&P 100 (VXO) or S&P 500 (VIX) (see, for instance, Bloom, 2009; Popp and Zhang, 2016), survey-based forecasts (Bachmann et al., 2013; Greig et al., 2018; Ozturk and Sheng, 2017) and news-related proxies (such as the uncertainty index by Baker et al., 2016). Jurado et al. (2015) suggest measuring uncertainty as the conditional volatility of the unpredictable component of a data-rich econometric model (see also Ludvigson et al., 2019). The latter is related to our approach, as we also use a number of macroeconomic and financial market variables to infer some form of aggregate uncertainty.

Our suggested measure of global macro-financial uncertainty is based on a simple test statistic that varies with deviations from historical mean and correlation patterns of macroeconomic and financial variables. Our methodology is in the spirit of the 'financial turbulence' measure of portfolio risk that has been proposed in the finance literature by Kritzman and Li (2010) based on work by Chow et al. (1999). Stöckl et al. (2017) and Stöckl and Hanke (2014) highlight the advantages of that measure over other commonly used financial risk measures and show how information from various different input factors can be aggregated across variables and regions. Building on this work, we adapt the methodology to trace macro-financial uncertainty at the global level using country-level macroeconomic and financial variables that are aggregated into a global macro-financial uncertainty (MFU) measure. This measure is well suited for our analysis for two main reasons. First, while most of the literature focuses on some form of country-specific uncertainty, we capture macroeconomic and financial uncertainty at the global level. Second, the construction of the measure allows us to quantify the contribution of individual input factors. This approach, in turn, enables us to evaluate the role of the origin of uncertainty, as outlined below in Section 4.2.

[1] We also confirm the validity of our results by considering other measures of uncertainty, including the uncertainty indices proposed by Davis (2016), Ludvigson et al. (2019) and Piffer and Podstawski (2018).

The intuition of our proposed measure of current macro-financial uncertainty can be illustrated by a simple t-statistic. Consider the deviation of the change in some short-term interest rate, ΔINT_t^{ST}, from its historical mean, measured in standard deviations: $\frac{\Delta INT_t^{ST} - \mu_{\Delta INT^{ST}}}{\sigma_{\Delta INT^{ST}}}$. Assuming a reasonable number of observations (e.g., 60 months) for the calculation of $\mu_{\Delta INT^{ST}}$ and $\sigma_{\Delta INT^{ST}}$, a magnitude above 2 is a 5% event (given the t_{59} distribution of the statistic) and would happen roughly once every two years. In a macroeconomic context, however, not only short-term interest rates but also changes in long-term interest rates, ΔINT^{LT}, may be relevant. A natural extension of the above is to calculate

$$\sqrt{\frac{\left(\Delta INT_t^{ST} - \mu_{\Delta INT^{ST}}\right)^2}{\sigma^2_{\Delta INT^{ST}}} + \frac{\left(\Delta INT_t^{LT} - \mu_{\Delta INT^{LT}}\right)^2}{\sigma^2_{\Delta INT^{LT}}}}.$$

This approach, however, neglects the fact that short- and long-term interest rates are usually correlated. The multivariate generalization of the t-statistic developed by Hotelling (1931), and therefore often called Hotelling's (1931) T-squared statistic, takes into account fluctuations in both measures as well as their direction:

$$\sqrt{(\mathbf{\Delta INT_t} - \hat{\boldsymbol{\mu}}_{\mathbf{\Delta INT}})' \hat{\boldsymbol{\Sigma}}^{-1}_{\Delta INT} (\mathbf{\Delta INT_t} - \hat{\boldsymbol{\mu}}_{\mathbf{\Delta INT}})},$$

where $\mathbf{\Delta INT_t}$ is the vector of current changes in long- and short-term interest rates in relation to their vector of means $\hat{\boldsymbol{\mu}}$, given their covariance matrix $\hat{\boldsymbol{\Sigma}}$. In this case, assuming a high positive correlation of both variables, the measure would indicate a low-probability event, in the domain of approximately 5%, given that both interest rates move one respective standard deviation in opposite directions. Hotelling's (1931) T-squared statistic increases in two dimensions: (1) if one realization deviates from the mean and (2) if the correlations in the contemporary variables deviate from their long-term comovement patterns.

For our measure of global macro-financial uncertainty, the set of variables that enters the index calculation comprises data from the G7 economies: the United States, Japan, Canada, and the United Kingdom, as well as Germany, France and Italy, which are summarized by Euro area aggregates. As we focus explicitly on macro-financial uncertainty and its effects on economic activity, we use the following macroeconomic and financial variables as inputs for the regional components of macro-financial uncertainty: As suggested by the Phillips curve relationship, we consider year-on-year growth rates of consumer price indices (CPI), i.e., inflation rates (INFL). To capture the current stance of monetary policy, we take into account the yields on 2- and 10-year government bonds (INT2Y, INT10Y). Additionally, to account for international competitiveness at the country level, we capture fluctuations in relative prices through changes in the real effective exchange rate (REER). To capture fluctuations in risk premia as well as aggregate levels of financial market risk, we include major stock indices (STOCKS) as well as the corresponding index of implied volatility (VIX). By capturing developments in prices, interest rates, exchange rates and financial market developments, we take into account the most commonly used variables in the context of simple macroeconomic models.[2] All variables for macro-financial uncertainty are taken from Bloomberg, with the exception of GDP, which we retrieve from the OECD. Table 1 shows the included variables and the respective data sources.

All variables are entered as first differences. As stock indices are entered in logs, we capture percentage changes in this case. We employ two further adjustments. First, the dependent variable, GDP growth, in the regression exercise below, in which we evaluate the effects of uncertainty, is quarterly. To take into account the quarterly frequency in the construction of our index, we use three-month moving averages of all input factors, $\bar{\mathbf{x}}_t = \frac{1}{3}\sum_{\tau=0}^{2}\mathbf{x}_{t-\tau}$.[3]

Below, we use end-of-quarter observations of the index in the regressions. Second, to calculate a global measure of macro-financial uncertainty, we combine all inputs weighting them by the respective GDP of each country (region), $w_{c,t}$. To ensure that the index maintains the distributional properties of the T-squared statistic, we follow Stöckl et al. (2017) and normalize the weights by their squared sum. Therefore, we define a diagonal matrix of adjusted weights as

[2] While the choice of the six variables is admittedly partly based on judgment and thus, to some extent, ad hoc, the aim is for the variables to cover the most important areas of (short-term) risk and uncertainty from a macro-financial perspective. Furthermore, the inclusion of additional variables (e.g., short-term proxies for economic activity or economic surprise indices) hardly changes the corresponding macroeconomic uncertainty indices at the country level. Based on these tests, we conclude that the six variables cover the most essential areas of macro-financial uncertainty for the respective country sample.

[3] The vector of variables is comprised of changes of these variables, stacked for all countries:

$$\mathbf{x} = \left(\begin{pmatrix} \Delta log(STOCKS_1) \\ \vdots \\ \Delta log(STOCKS_n) \end{pmatrix}', \begin{pmatrix} \Delta VIX_1 \\ \vdots \\ \Delta VIX_n \end{pmatrix}', \begin{pmatrix} \Delta INFL_1 \\ \vdots \\ \Delta INFL_n \end{pmatrix}', \begin{pmatrix} \Delta INT2Y_1 \\ \vdots \\ \Delta INT2Y_n \end{pmatrix}', \begin{pmatrix} \Delta INT10Y_1 \\ \vdots \\ \Delta INT10Y_n \end{pmatrix}', \begin{pmatrix} \Delta REER_1 \\ \vdots \\ \Delta REER_n \end{pmatrix}' \right)',$$

where $c = 1, \dots, n$ are the $n = 5$ countries (regions) that we consider in the calculation of the index.

Table 1
Input variables used for macro-financial uncertainty.

Variables	Bloomberg Code	start date	end date
US_STOCKS	SPX	02/1990	03/2019
US_VIX	VIX	02/1990	03/2019
US_INFL	CPI	02/1990	03/2019
US_INT10Y	USGG10YR	02/1990	03/2019
US_INT2Y	USGG2YR	02/1990	03/2019
US_REER	BISBUSR	01/1994	03/2019
EA_STOCKS	SX5E	02/1990	03/2019
EA_VIX	V2X	01/1999	03/2019
EA_INFL	ECCPEMUY	01/1997	03/2019
EA_INT10Y	EUGB10	02/1990	03/2019
EA_INT2Y	EUGB2	02/1990	03/2019
EA_REER	BISBEUR	01/1994	03/2019
JP_STOCKS	NKY	02/1990	03/2019
JP_VIX	VNKY	01/2001	03/2019
JP_INFL	JNCPIYOY	02/1990	03/2019
JP_INT10Y	GTJPY10YR	02/1990	03/2019
JP_INT2Y	GTJPY2YR	02/1994	03/2019
JP_REER	BISBJPR	01/1994	03/2019
CA_STOCKS	SPTSX	02/1990	03/2019
CA_INFL	CACPIYOY	02/1990	03/2019
CA_INT10Y	GTCAD10YR	02/1990	03/2019
CA_INT2Y	GTCAD2YR	02/1990	03/2019
CA_REER	BISBCAR	01/1994	03/2019
UK_STOCKS	UKX	02/1990	03/2019
UK_VIX	VFTSE	01/2000	03/2019
UK_INFL	UKRPCJYR	02/1990	03/2019
UK_INT10Y	GTGBP10YR	01/1992	03/2019
UK_INT2Y	GTGBP2YR	01/1992	03/2019
UK_REER	BISBGBR	01/1994	03/2019

Notes: This table reports variables (country '_' variable), Bloomberg Code and start/end date for all input variables. We use data from the United States (US), the Euro area (EA), Japan (JP), Canada (CA) and the United Kingdom (UK). Variables used are the major regional stock market index (STOCKS, namely, the S&P 500, EuroStoxx 50, NIKKEI225, S&P/TSX Composite and FTSE 100), its implied volatility index (if available, VIX), the inflation (CPI) rate (INFL), the 2- and 10-year government bond yields (INT2Y, INT10Y) and the real effective exchange rate (REER) calculated by the BIS.

$\mathbf{w_t^*} = diag\left(\frac{\mathbf{w}_t}{\sum_{j\in\mathcal{S}} w_{j,t}^2}\right)$, where $\mathbf{w_t}$ is the vector of GDPs and $\mathcal{S}$ is the set of all input variables with cardinality $N = 30$.[4] Our index of global macro-financial uncertainty is thus defined as:

$$\mathrm{MFU}_{t,\mathrm{global}} := \sqrt{(\mathbf{w_t^*}(\bar{\mathbf{x}}_\mathbf{t} - \hat{\boldsymbol{\mu}}_\mathbf{x}))'\hat{\boldsymbol{\Sigma}}_x^{-1}(\mathbf{w_t^*}(\bar{\mathbf{x}}_\mathbf{t} - \hat{\boldsymbol{\mu}}_\mathbf{x}))}, \tag{1}$$

where $\bar{\mathbf{x}}_\mathbf{t}$ is the vector of inputs at time t. For the calculation of macro-financial uncertainty, we take into account that not all variables are available from the beginning of our sample period (see Table 1 column 3 for information regarding each series' starting date) and rescale the measure accordingly. We use full sample statistics for the calculation of $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ in Eq. (1).[5]

In Fig. 1, we compare our measure of macro-financial uncertainty with four other uncertainty measures: measures of macroeconomic (Jurado et al., 2015) and financial (Ludvigson et al., 2019) uncertainty[6]; the Davis (2016) Global Economic Policy Uncertainty Index,[7] which summarizes the Baker et al. (2016) measure of economic policy uncertainty at the global scale; and uncertainty shocks measured using fluctuations in the gold price as proposed by Piffer and Podstawski (2018).[8] Additionally, NBER recessions are highlighted in gray, and important economic events that occurred throughout our sample period are

[4] We use the same weight for all input variables from the respective country such that $w_{j,t} = w_{c,t}, \forall j \in \mathcal{S}|_c$.

[5] In the robustness checks, we also employ a version of macro-financial uncertainty that only takes into account information that is available at the corresponding date through a recursively growing window for the calculation of $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$. To this effect, we use a starting window of 120 months and let variables that have shorter time series only enter into the calculation once more than 60 observations are available.

[6] Provided by Sydney Ludvigson on her website sydneyludvigson.com. We use the version for forecasting horizon $h = 1$.

[7] Provided by the author on the website policyuncertainty.com. We use the version with PPP weighting.

[8] Provided by Michele Piffer on his website sites.google.com/site/michelepiffereconomics.

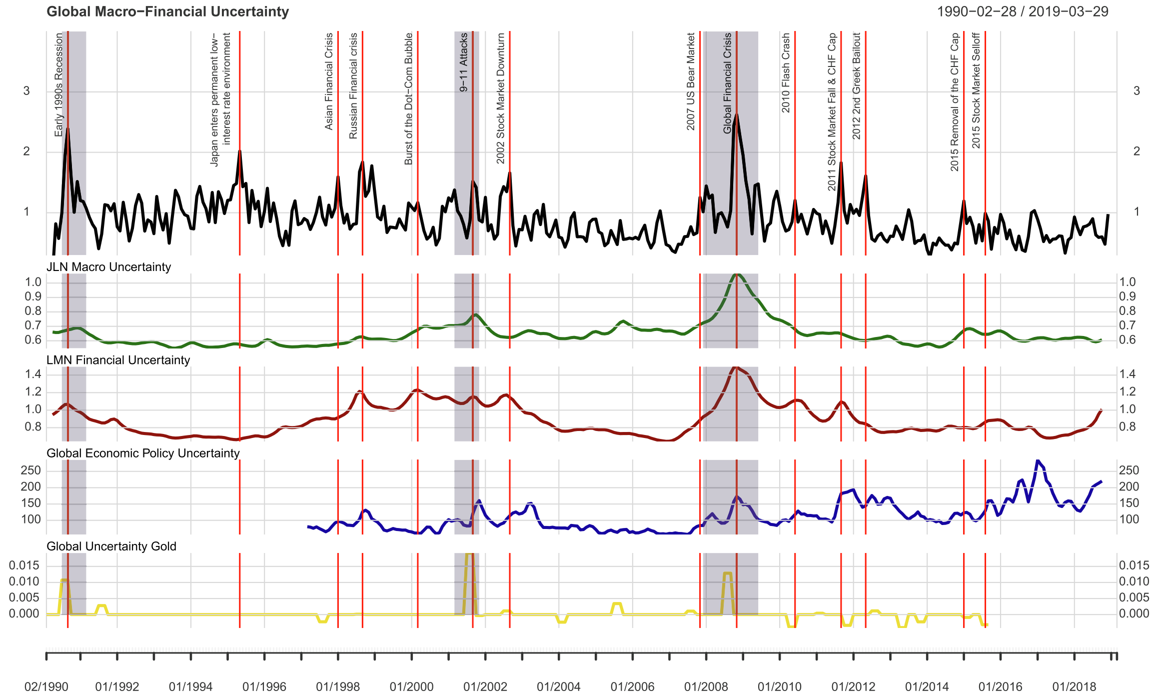

Fig. 1. Global macro-financial uncertainty and alternative measures of global macroeconomic uncertainty. Notes: This figure depicts four different measures of macroeconomic uncertainty: our macro-financial uncertainty measure, the Jurado et al. (2015) macroeconomic and the Ludvigson et al. (2019) financial uncertainty index (for a horizon of $h = 1$), the Baker et al. (2016) Global Economic Policy Uncertainty Index, and the Piffer and Podstawski (2018) uncertainty shocks using fluctuations in the price of gold. We also highlight NBER recessions in gray and indicate and label certain economic events of global influence with a red line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

also labeled accordingly. Remarkably, our measure of MFU reacts quickly and traces major events with a narrative of high uncertainty quite well, as shown by the spikes in global macro-financial uncertainty (indicated by the red lines in Fig. 1). Alternative measures of uncertainty proposed in the literature show comparatively less variability and – in some instances – a considerable delay in reaction to high-uncertainty events.[9] Overall, the index is well suited to picking up high-uncertainty episodes in recent decades in line with the narrative of the respective time periods, making it particularly attractive for the application in our study.

At the same time, it is also important to outline the limitations of our measure of macro-financial uncertainty. While the model assumptions of our measure are quite minimal, as the indicator can be calculated mechanically for any class of variables or time period, the choice of the time period for the calculation of means and variance-covariance matrix as well as the assumption of a constant $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ are two important assumptions that have to be taken into account in the interpretation of the index. This also implies that the measure partly uses information that is only available ex post, as the means and the variance-covariance matrix are calculated for the whole sample period. Nevertheless, the assumptions remain quite limited compared to those of alternative model-based measures of uncertainty, and the index is easily replicable as its construction is straightforward. Moreover, one of our robustness checks in Section 5 explicitly evaluates the sensitivity of the results with respect to the use of full-sample moments by calculating a variant of MFU based on recursive windows. As shown below, the results are qualitatively unchanged when loosening this specific modeling assumption.

Table 2 shows the correlations of our measure of macro-financial uncertainty with the alternative measures of uncertainty shown in Fig. 1. We observe positive correlations with all measures, although the correlations with global economic uncertainty and uncertainty from gold trading are very low.

3. Empirical approach to evaluate uncertainty

To address our research question, we evaluate the effects of global macro-financial uncertainty using local projections put forward by Jordà (2005). The local projections method allows us to estimate state-dependent impulse response functions in a flexible and parsimonious way that is robust to misspecification. We estimate models of the type

[9] Note that the Ludvigson et al. (2019) measures of macroeconomic and financial uncertainty are only calculated for the US.

Table 2
Correlations of macro-financial uncertainty with alternative uncertainty measures.

	Uncertainty measures			
	Macro-financial	JLN macro	LMN financial	Global economic policy
JLN macro	0.27			
LMN financial	0.37	0.67		
Global EP	0.13	−0.02	−0.02	
Gold market	0.11	0.33	0.25	0.02

Notes: This table reports correlations between our measure of macro-financial uncertainty and alternative uncertainty measures: Jurado et al. (2015) macro uncertainty, Ludvigson et al. (2019) financial uncertainty, Davis (2016)'s measure of Global Economic Policy Uncertainty and the Piffer and Podstawski (2018) measure of uncertainty based on gold trading.

$$y_{i,t+h} = S_{i,t-1} + \beta_h \mathrm{MFU}_t + \sum_{\tau=1}^{2}(\gamma_h \mathrm{MFU}_{t-\tau} + \delta_h y_{i,t-\tau}) + S_{i,t-1}\left(\beta_{S,h}\mathrm{MFU}_t + \sum_{\tau=1}^{2}\left(\gamma_{S,h}\mathrm{MFU}_{t-\tau} + \delta_{S,h} y_{i,t-\tau}\right)\right) + \alpha_{i,h} + \lambda_{1,h} t + \lambda_{2,h} t^2 + \epsilon_{i,t+h}, \quad (2)$$

for each horizon h and for the sample period 1990q1 to 2012q4.[10] The dependent variable is the quarterly annualized growth rate of gross domestic product (GDP) of each of the 24 OECD countries measured in purchasing power parities (PPPs). The dummy variable, $S_{i,t-1}$, is constructed from the Romer and Romer (2017) banking sector distress index. For each country i, the index captures disruptions of credit intermediation in the spirit of Bernanke (1983). Thus, an increase in the index can be interpreted as an adverse credit supply disruption. The dummy $S_{i,t-1}$ takes a value of 1 when banking sector distress is larger than 0.[11] The dummy enters the regression equation with period $t-1$ to alleviate endogeneity issues and to pick up the state of credit intermediation at the time the shock sets in. In addition, we use a continuous version of $S_{i,t-1}$ in a robustness check. As MFU_t takes into account the most recent three months by construction, we use end-of-quarter observations. Also note that we include the contemporaneous value of MFU_t, while the control variables are entered with a one-period lag. We use lags up to $\tau = 2$. Our specification replicates the recursive structure in SVARs with the risk or uncertainty measure ordered first (Bloom, 2009; Leduc and Liu, 2016; Basu and Bundick, 2017). The shock in global macro-financial uncertainty is simply given by the coefficients of MFU_t. In effect, we assume that global macro-financial uncertainty is predetermined with respect to GDP growth at the country level.[12] In addition, we include multiplicative terms of $S_{i,t-1}$ with MFU_t and the lagged dependent variable to allow for nonlinearities in the responses associated with the state of the banking sector. We also control for country fixed effects and a linear and quadratic time trend.

One complication associated with the Jordà method is the serial correlation in the error terms induced by the successive leading of the dependent variable. To take into account the respective serial correlation, we use the Newey-West correction of the standard errors adjusting for h lags.

The impulse response functions presented below in a state of no banking sector distress are calculated based on the sequences of the estimated β_h coefficients. The impulse response functions to surges in MFU_t in states of banking sector distress are the sequences of $(\beta_h + \beta_{S,h})$.[13]

4. Results

4.1. Baseline estimation

As a first step of our analysis, we estimate Eq. (2) using a panel of 24 OECD countries. Fig. 2 shows the impulse response functions of annual GDP growth to a one-standard-deviation surge in macro-financial uncertainty in the linear model ignoring state dependency, as well as in states of well-functioning and impaired credit intermediation. The gray shaded areas represent the 95% confidence bands. In addition, we plot the t-statistics for the null hypothesis, $\beta_{S,h} = 0$, to evaluate whether the impulse responses within and outside states of banking sector distress are identical.

We first consider the responses of GDP growth to global macro-financial uncertainty in the linear model; i.e., $S_{i,t-1}$ is set to zero throughout the whole sample. Uncertainty immediately leads to a significant and negative effect on output in line with

[10] The sample is constrained by the availability of data for the construction of the global macro-financial uncertainty measure and the availability of the Romer and Romer (2017) banking sector distress measure.

[11] The index takes values between 0 and 15. The majority of the observations are zeros (approximately 90% of the sample), indicating that credit intermediation is well functioning in general. The index is biannual, and we use the biannual observation for two quarters.

[12] Note that in our setting, the recursive ordering assumption is additionally supported by the calculation of our global uncertainty measure at the global scale. In addition, we relax this assumption in a robustness exercise in which we run country-specific macro-financial uncertainty calculations for those countries that are considered in the calculation of MFU. Specifically, we leave, e.g., the US out of consideration when we calculate MFU for the US (and do the same for the UK, Japan, Canada and euro area countries).

[13] Note that any effect that is only due to banking sector distress (i.e., which is orthogonal to global macro-financial uncertainty) is captured by the coefficient of $S_{i,t-1}$.

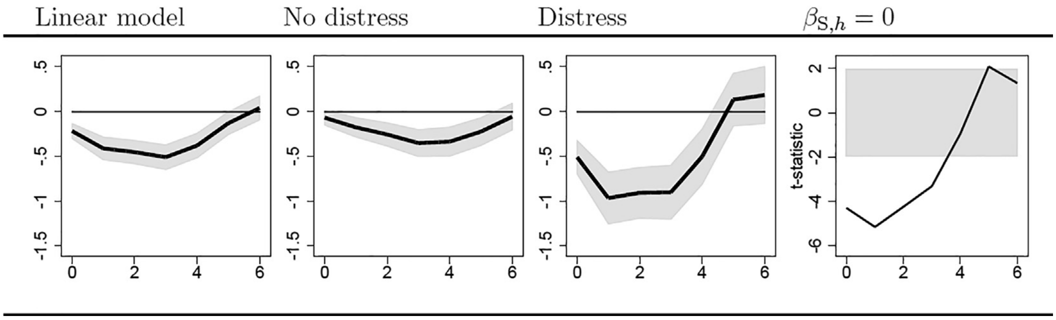

Fig. 2. Responses of real GDP growth in percent to global macro-financial uncertainty. Notes: From left to right, we show the responses of real GDP growth in a linear model, in a state of no banking sector distress and in a state of banking sector distress. In addition, we show the t-statistic corresponding to $\beta_{S,h} = 0$. The gray-shaded areas represent the 95% confidence intervals. The horizontal axis is in quarters.

the consensus view in the literature. While the peak of the response is reached at −0.51 percentage points three quarters after the shock sets in, uncertainty reduces growth rates for approximately one-and-a-half years.

By introducing interaction terms, we now consider uncertainty shocks that coincide with a healthy banking sector (second column) as opposed to shocks that hit the economy in a state of financial sector distress (third column). The comparison between the two impulse response functions clearly shows that uncertainty has much stronger adverse effects in a state of banking sector distress, especially in the first year after the shock sets in, with the impulse responses being significantly different across the two states and the t-statistics for the null $\beta_{S,h} = 0$ well above an absolute value of 2. In states of banking sector distress, the effects of global macro-financial uncertainty on GDP growth are approximately three times larger than that of responses in states of no banking sector distress and almost twice as large as the responses in the linear model. The maximum impact amounts to −0.96 percentage points of annual GDP growth in a state of banking sector distress, while the maximum impact in a state in which the banking system is well functioning is −0.35 percentage points. From Fig. 2, it thus becomes evident that allowing for the nonlinearity in the responses associated with the current state of credit intermediation allows us to distinguish between cases where uncertainty has only moderately negative effects on the one hand and those where uncertainty exerts strong adverse effects on the economy on the other. This distinction is particularly important from a policy perspective, as the separation of states of functioning and stressed credit intermediation reveals episodes of higher vulnerability, as we will discuss in more detail below.

4.2. Disentangling macroeconomic and financial uncertainty

The design of our measure of global macro-financial uncertainty allows us to compute the contributions of each included variable to the overall level of the index at any point in time. We sum the contributions of the financial as well as the macroeconomic variables to build two subindices, whose sum, in turn, gives the overall index. This approach allows us to learn whether a specific class of variables that enter the macro-financial uncertainty calculation, rather than the entire set of variables, drives the results.

To investigate the contributions of each incorporated input, we apply the following relation: $a'\Omega^{-1}a = \sum_{j=1}^{K} a'\Omega \circ a' = \sum_{j=1}^{K} (a'\Omega_{-,1}\, a_1, \ldots, a'\Omega_{-,K}\, a_K) = \sum_{j=1}^{K}\sum_{i=1}^{K} a_i \Omega_{i,j} a_j$, where a is some $K \times 1$-vector, Ω is some $K \times K$ matrix and the elementwise multiplication is denoted by $\circ$. In turn, each $a'\Omega_{-j} \cdot a_j$ is the contribution of element j. Using this notation, we rewrite Eq. (1) as

$$\mathrm{MFU}_{t,\mathrm{global}} :== \sqrt{\begin{array}{l}\displaystyle\sum_{j\in\mathcal{S}_M}\left(\left(\mathbf{w}_\mathbf{t}^*(\bar{\mathbf{x}}_\mathbf{t} - \hat{\boldsymbol{\mu}}_\mathbf{x})\right)'\hat{\boldsymbol{\Sigma}}_x^{-1} \circ \left(\mathbf{w}_{\mathbf{j},\mathbf{t}}^*\left(\bar{\mathbf{x}}_{\mathbf{j},\mathbf{t}} - \hat{\boldsymbol{\mu}}_{\mathbf{x}_\mathbf{j}}\right)\right)\right) \\ \displaystyle+\sum_{j\in\mathcal{S}_F}\left(\left(\mathbf{w}_\mathbf{t}^*(\bar{\mathbf{x}}_\mathbf{t} - \hat{\boldsymbol{\mu}}_\mathbf{x})\right)'\hat{\boldsymbol{\Sigma}}_x^{-1} \circ \left(\mathbf{w}_{\mathbf{j},\mathbf{t}}^*\left(\bar{\mathbf{x}}_{\mathbf{j},\mathbf{t}} - \hat{\boldsymbol{\mu}}_{\mathbf{x}_\mathbf{j}}\right)\right)\right),\end{array}} \tag{3}$$

where we split the set of variables $\mathcal{S} = \mathcal{S}_M \cup \mathcal{S}_F$ into macroeconomic $\mathcal{S}_M$ (short- and long-term interest rates, inflation rates and the real effective exchange rate) and financial $\mathcal{S}_F$ (stock index and stock market volatility) variables. Fig. 3 shows the contributions of macroeconomic (green area) and financial (red area) variables to MFU. Both groups of variables – macroeconomic and financial market measures – play an important role for the level of MFU. However, the majority of larger spikes in the variability of the index seem to be driven by the financial market variables. This is especially true for the Russian financial crisis (1998), the stock market downturn in 2002, the outbreak of the global financial crisis, and the stock market selloff in 2015; this behavior is not surprising because these events have a financial narrative. In contrast, the contributions of the block of macroeconomic variables dominate during normal times and, e.g., in the recession in the early 1990s, Japan's entry into a permanent low-interest rate environment in 1995, the bursting of the dotcom bubble and the 9–11 attacks.

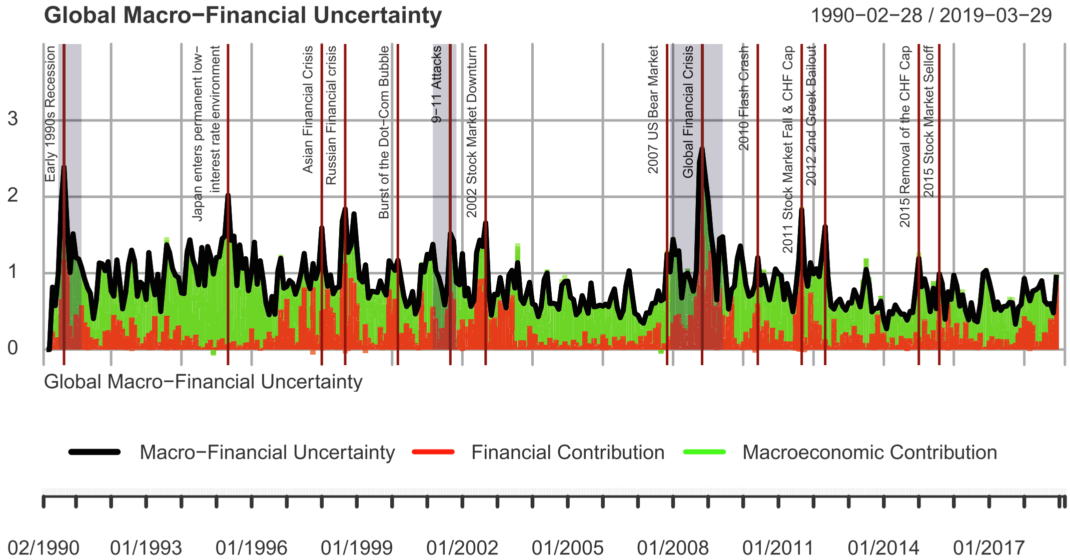

Fig. 3. Global macro-financial uncertainty together with the contributions of macroeconomic and financial market variables Notes: This figure depicts our macro-financial uncertainty measure, additionally reporting the contributions of macroeconomic and financial market variables. We also highlight NBER recessions in gray and indicate and label certain economic events of global influence with a red line. Note that some of the contributions to the overall index can be negative; see Section 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Conceptually, this separation of dimensions of uncertainty is related to Ludvigson et al. (2019). The authors generate measures of macroeconomic and financial uncertainty in the spirit of Jurado et al. (2015) and evaluate how shocks to these measures affect US real economy activity in a structural vector autoregression (VAR) framework. While their approach is useful for studying the extent to which uncertainty endogenously reacts to business cycle fluctuations, our approach is less restrictive in terms of the identification assumptions.[14,15]

Fig. 4 shows the responses of real GDP growth to one-standard-deviation fluctuations in global financial (Panel A) and macroeconomic (Panel B) uncertainty. The patterns across the two measures of uncertainty are quite similar. Uncertainty exerts significantly stronger adverse effects on economic activity in a state of distressed credit intermediation in both cases, which further supports the generality of our results. At same time, however, we observe that while macro uncertainty also exerts strong and significant adverse effects, they are relatively more pronounced if uncertainty is associated with financial market developments. The maximum impact of financial uncertainty is almost twice as large as that of macroeconomic uncertainty. Notably, using US data, Ludvigson et al. (2019) report that while financial uncertainty shocks lead to pronounced negative effects on economic activity, macro uncertainty does not lead to recessionary effects in the short run, even though it amplifies recessions. While the former finding is in line with our results, using our methodology and a set of OECD countries, we do find recessionary short-run effects of macroeconomic uncertainty as well.

4.3. Country-by-country estimations

A further aspect that is of particular interest in our context is cross-country differences. Countries may be affected to different degrees by surges in global macro-financial uncertainty depending on the level of openness, the level of integration of financial markets, fiscal and monetary policy space, etc. In the next step of our analysis, we look at potential heterogeneities in the responses to global macro-financial uncertainty by estimating Eq. (2) country by country.

To reveal heterogeneities across countries' responses, Fig. 5 shows the mean responses of all 24 OECD countries, thereby distinguishing between periods with (solid lines) and periods without (dashed lines) banking sector distress. The results of the panel estimation are confirmed across the board, i.e., the effects of macro-financial uncertainty are more pronounced in the event of banking sector distress in the vast majority of countries for which we run the country-by-country estimations. In particular, Greece and Norway appear to be the only exceptions, as we do not observe that surges in global macro-financial uncertainty are more harmful in periods of banking sector distress in these countries. However, for these countries, the uncertainty effects can only be estimated imprecisely when taking into account the respective error bands.

[14] First, in Ludvigson et al. (2019), financial and macroeconomic shocks are orthogonal by construction, although some historical events may have caused uncertainty concerning real economic and financial market developments at the same time. Second, they identify macro and financial uncertainty shocks by imposing constraints on the VAR shock series based on narrative accounts, while our approach is data driven in the sense that we do not have to take a stance on whether an event primarily leads to macro or financial uncertainty.

[15] Note that the endogeneity issue in regards to macroeconomic uncertainty, which is suggested by the results in Ludvigson et al. (2019), does not apply in our case. We measure macroeconomic uncertainty at the global scale, which supports the predeterminedness assumption.

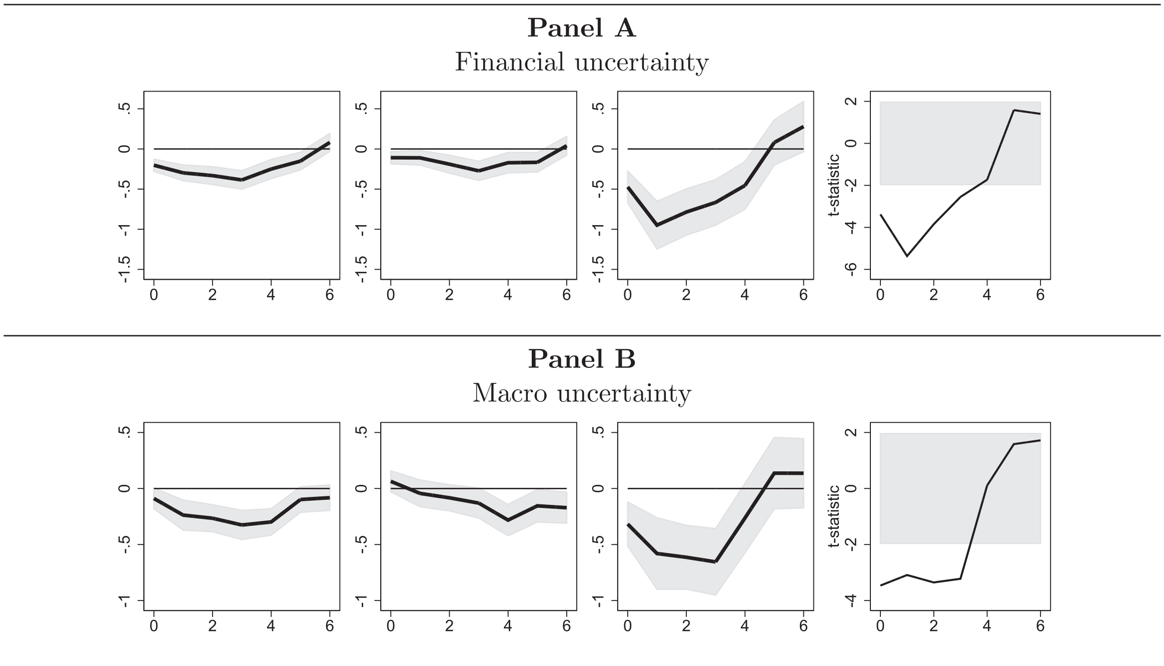

Fig. 4. Responses of real GDP growth – financial vs. macro uncertainty. Notes: From left to right, we show the responses of real GDP growth in a linear model, in a state of no banking sector distress and in a state of banking sector distress. In addition, we show the t-statistic corresponding to $\beta_{S,h} = 0$. The gray-shaded areas represent the 95% confidence intervals. The horizontal axis is in quarters.

The reason behind this surprising finding can be better understood when taking into account the historical context. In particular, since Greece entered a state of stressed credit intermediation in the global financial crisis and has remained in this state ever since, distinguishing between the two effects is empirically difficult, as the sample is simply divided into a 'pre-crisis' and 'post-crisis' period in the case of Greece. In a similar vein, the differences across other stressed European economies are also less pronounced, as some countries (e.g., Portugal, Spain, and Italy) have remained in a state of distressed credit intermediation since the onset of the global financial crisis. In contrast, Norway has only experienced two relatively short periods of banking sector distress, namely, during the Nordic crisis at the start of the 1990s and during the global financial crisis. In countries where periods of banking sector distress have been relatively short (in addition to Norway, this is the case for Australia, Luxembourg, Belgium and the Netherlands), the identification of the effect in times of banking sector distress seems to be difficult, leading to a smaller 'gap' in terms of magnitude between the two states of the banking sector.

On the other hand, differences in the responses depending on the state of credit intermediation are particularly pronounced for Ireland, Iceland, New Zealand, Sweden, Turkey (at least initially), Finland, and Germany. Overall, we therefore conclude that the effect is quite robust across individual countries.

5. Robustness analyses

We now present robustness checks that evaluate potential sensitivities regarding the construction of global macro-financial uncertainty and the specification of the regression model. Fig. 6 summarizes these checks.

We first consider Panel A of Fig. 6. Countries that enter the calculation of the uncertainty measure are also part of the sample that we use in the regression analysis. Thus, endogeneity problems may arise, even though (i) we leave economic activity out of consideration of the measurement of uncertainty and (ii) the uncertainty measure traces second- rather than first-moment developments. To alleviate this issue, we calculate specific uncertainty measures for those countries that are part of the MFU calculation. Thus, we calculate separate measures for the US, the UK, Japan, Canada and the euro area economies and leave the respective country out of consideration. More precisely, when estimating the effects of macro-financial uncertainty for the US, MFU is calculated without the US, and we proceed in a similar way for the other countries. Looking at Panel A, we see that the results are not affected by this revised calculation of the measure, suggesting that our baseline estimates do not suffer from endogeneity issues.

As a second robustness check, we reestimate the baseline model using a (semi) continuous state variable instead of a dummy that captures banking sector distress. The Romer and Romer (2017) measure ranges from 0 to 15, with most of the observations being 0 (see above). We use this measure directly instead of the dummy and evaluate the interaction term

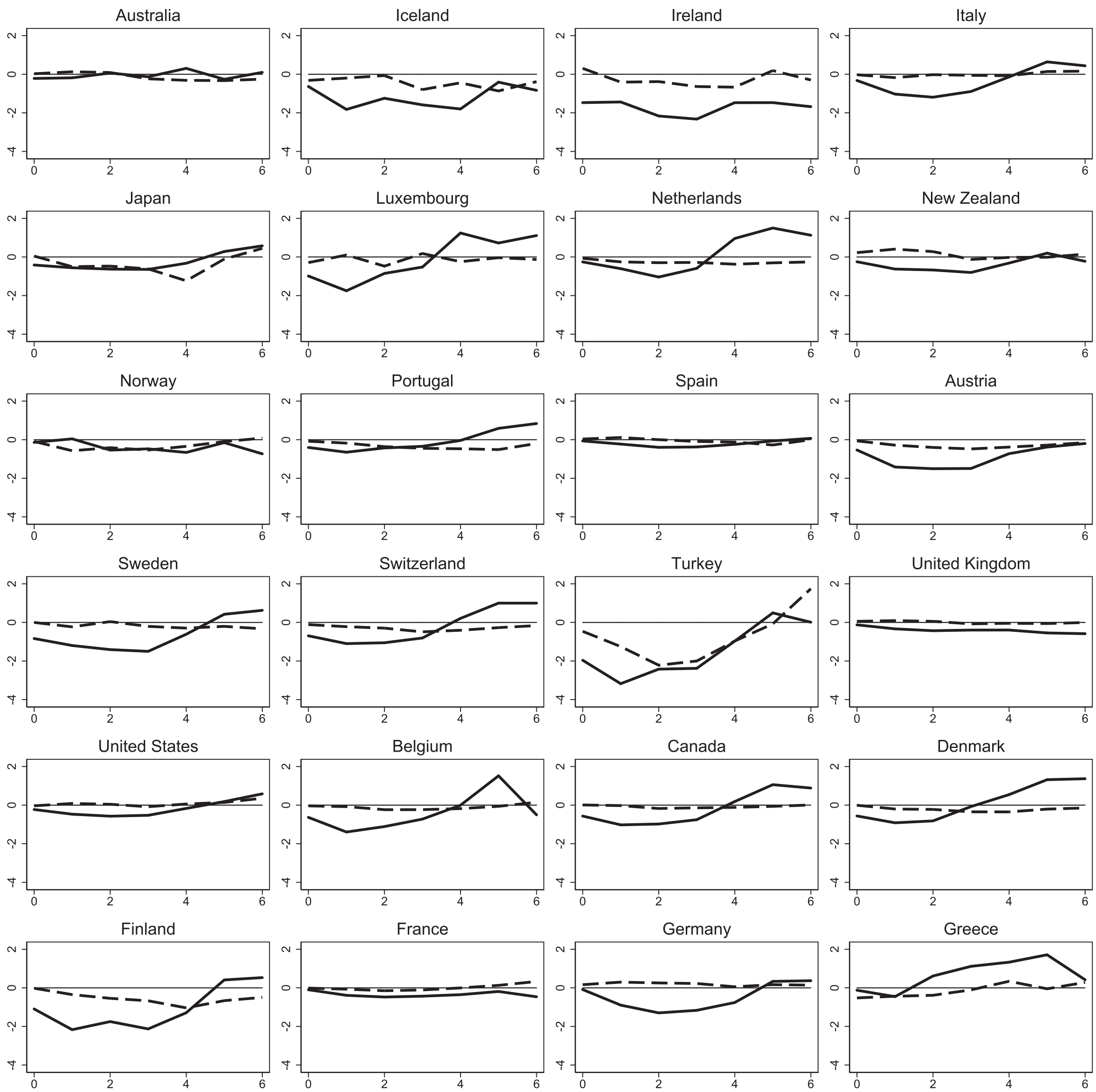

Fig. 5. Responses of real GDP growth – individual countries. The solid lines represent the mean responses inside and the dashed lines the mean responses outside states of distressed credit intermediation. The horizontal axis is in quarters.

at a level of 7, which is the level Romer and Romer (2017) classifies as a crisis scenario. Panel B of Fig. 6 shows that the results remain qualitatively unchanged with respect to our baseline estimations.

Finally, we show the results of an estimation in which we use a variant of MFU that is calculated from recursive windows (Panel C). In the baseline calculation of MFU, we use a constant mean and constant covariance matrix that are calculated from the full sample. In this sense, the measures contain forward-looking information. To explore the robustness of our measure with respect to this modeling assumption, we use a recursive window estimation starting with an initial calculation period of 120 months, as mentioned before. Once again, our baseline results are qualitatively unaffected.

In addition to these tests with respect to the modeling of macro-financial uncertainty and the specification of the state variable, we test the generality of our results using alternative uncertainty measures put forward in the literature. The results are summarized in Fig. 7.

We first compare our results with the effects of the economic policy uncertainty (EPU) measure of Davis (2016), shown in Panel A of Fig. 7. This measure also fits our estimation and identification strategy, as it does not directly pick up banking

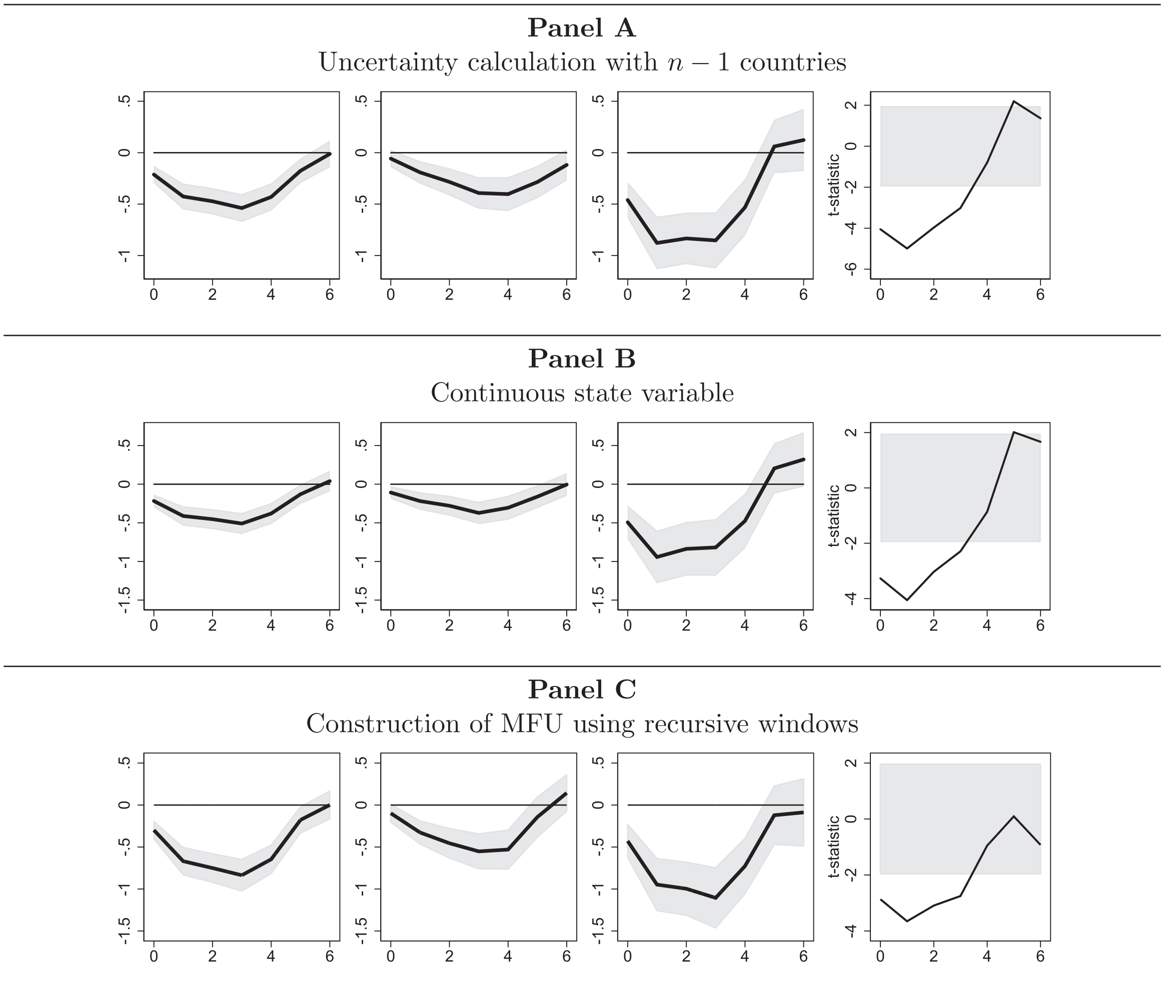

Fig. 6. Responses of real GDP growth – Robustness analyses. From left to right we show the responses of real GDP growth in linear model, in a state of no banking sector distress and in a state of banking sector distress. In addition, we show the t-statistic corresponding to $\beta_{S,h} = 0$. The grey-shaded areas represent 95 percent confidence intervals. The horizontal axis is in quarters.

sector distress and tracks uncertainty at the global level. The impulse response functions to a one-standard-deviation increase in EPU are estimated from regression model (2). It is evident that the implications are qualitatively similar. As expected, banking sector distress also matters for the transmission of uncertainty as measured by the EPU index, i.e., political uncertainty.

Second, we apply our estimation methodology using the proxy for global uncertainty put forward by Piffer and Podstawski (2018), shown in Panel B of Fig. 7. They measure uncertainty using the variations in the price of gold around events associated with unexpected changes in uncertainty. This measure should capture uncertainty shocks because gold is widely known as a safe haven asset. At the same time, at the global level, the gold price should be, to a large extent, contemporaneously predetermined with respect to country-level banking sector distress, which supports our identification assumptions. The responses of annual GDP growth to a one-standard-deviation surge in the Piffer and Podstawski (2018) uncertainty measure exhibit patterns that are consistent with our baseline results, thus confirming the significance of the effects of uncertainty on the state of the banking sector.

Finally, we evaluate the effects of the financial uncertainty measure put forward by Ludvigson et al. (2019).[16] While this measure has some conceptual similarities with the global financial uncertainty measure we propose, it is constructed based on US variables, and due to data limitations, it cannot easily be replicated for other countries. However, the Ludvigson et al. (2019) financial uncertainty measure reflects international developments to the extent that US uncertainty spills over to the global

[16] We refrain from showing estimates using the Jurado et al. (2015) macroeconomic uncertainty measure, however, due to potential endogeneity issues. Ludvigson et al. (2019) show that macroeconomic uncertainty is, rather, an endogenous reaction to business cycle developments than a cause of business cycle fluctuations. The estimations using the Jurado et al. (2015) show, however, state-dependent patterns consistent with our baseline estimates.

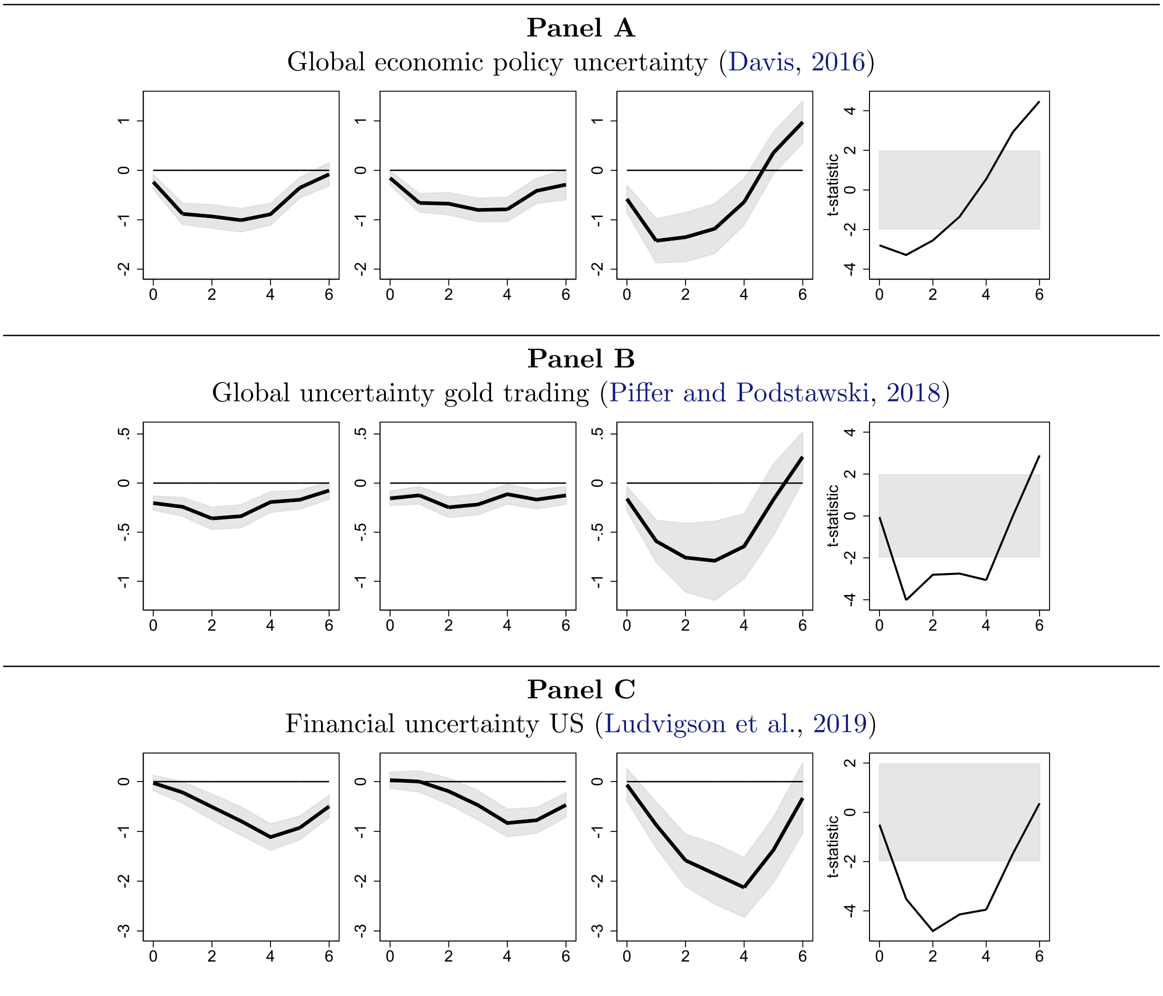

Fig. 7. Responses of real GDP growth – alternative uncertainty measures. Notes: From left to right, we show the responses of real GDP growth in a linear model, in a state of no banking sector distress and in a state of banking sector distress. In addition, we show the t-statistic corresponding to $\beta_{S,h} = 0$. The gray-shaded areas represent the 95% confidence intervals. The horizontal axis is in quarters.

economy, which makes it worthwhile to study its effects in our context. Panel C in Fig. 7 shows how GDP growth reacts to a one-standard-deviation surge in US financial uncertainty in the linear model as well as in the two different states of credit intermediation. While it is evident that with respect to the Ludvigson et al. (2019) financial uncertainty measure, we again observe stronger effects when credit intermediation is disturbed, we find that the effects of uncertainty are slightly deferred with practically no immediate response. This observation indicates that the propagation of uncertainty that originates in one country, in this case the US, to the rest of the world, exhibits a certain lag. Nevertheless, our main results are confirmed once again when using the alternative Ludvigson et al. (2019) financial uncertainty measure.

6. Conclusion

In this paper, we put forward a new measure of global macro-financial uncertainty and study its effects on GDP growth in a panel of 24 OECD countries. To evaluate the effects of surges in macro-financial uncertainty, we use local projections and allow for nonlinearities in the responses of GDP growth with regard to the state of the respective banking sector at the country level. While we find that uncertainty generally does have an adverse impact on economic growth in a sample of advanced (OECD) economies, the magnitude of the effect strongly depends on the state of the banking sector, suggesting that an uncertainty shock is strongly reinforced when credit intermediation is distressed. Furthermore, we find that the origin of uncertainty is important for its transmission.

Our results therefore suggest a key role of the financial view of the transmission of uncertainty. This suggestion, in turn, implies that a healthy banking sector increases systemic resilience vis-á-vis uncertainty shocks. Our paper contributes to the literature by explicitly distinguishing between macroeconomic and financial market uncertainty on the one hand and the state of financial intermediation on the other.

Our results have broader implications for policy-makers. In particular, the results imply that certainty about future policies is especially important in the context of distressed credit intermediation, as uncertainty shocks are approximately three times more harmful in such a macroeconomic environment compared to cases where the banking sector is well functioning. From a policy perspective, uncertainty typically surges when policy-makers tackle structural issues in the context of economic policy, e.g., issues related to trade, labor markets or competition policies. While such structural reforms are typically initiated in crisis periods when the sovereign is confronted with serious funding issues and higher bond spreads, our results suggest that structural reforms should rather be implemented in relatively calm periods characterized by a healthy banking sector, as such attempts at reform typically lead to a surge in uncertainty. While the translation of these results might be difficult at the national level, as strategic thinking implies a low probability that unpopular structural reforms are implemented in good times by politicians who want to be reelected, the results are relevant for international lenders such as the International Monetary Fund (IMF), as the implementation of difficult structural reforms may be less costly and thus more rewarding if these reforms are postponed to a period when the banking sector is no longer distressed. While the costs in terms of output loss could be reduced in such a case, the practical problem of the enforcement of these reforms – long after the lending has taken place – admittedly remains a practical hurdle.

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