

Measuring Macroeconomic Uncertainty: A Cross-Country Analysis

Working Paper

Author(s):

[Dibiasi, Andreas](#) ; Sarferaz, Samad

Publication date:

2020-06

Permanent link:

<https://doi.org/10.3929/ethz-b-000420180>

Rights / license:

[In Copyright - Non-Commercial Use Permitted](#)

Originally published in:

KOF Working Papers 479

KOF Swiss Economic Institute

**Measuring Macroeconomic Uncertainty:
A Cross-Country Analysis**

Andreas Dibiasi and Samad Sarferaz

KOF Working Papers, No. 479, June 2020

KOF

ETH Zurich
KOF Swiss Economic Institute
LEE G 116
Leonhardstrasse 21
8092 Zurich, Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

Measuring Macroeconomic Uncertainty: A Cross-Country Analysis*

Andreas Dibiasi[†] Samad Sarferaz[‡]

June 3, 2020

Abstract

This paper constructs internationally consistent measures of macroeconomic uncertainty. Our econometric framework extracts uncertainty from revisions in data obtained from standardized national accounts. Applying our model to quarterly post-WWII real-time data, we estimate macroeconomic uncertainty for 39 countries. The cross-country dimension of our uncertainty data allows us to identify the effects of uncertainty shocks on economic activity under different employment protection legislation. Our empirical findings suggest that the effects of uncertainty shocks are stronger and more persistent in countries with low employment protection compared to countries with high employment protection. These empirical findings are in line with a theoretical model under varying firing cost.

JEL classifications: C51, C53, C82, E32, J8

Keywords: Uncertainty Shocks, Real-Time Data, Rational Forecast Error, System of National Accounts, Employment Protection Legislation

*We are grateful to Alexander Rathke, Michael Siegenthaler, Gregor von Schweinitz, the participants of the Economics Research Seminar at Leipzig University for very helpful comments. We thank Tino Berger, Todd E. Clark, and Haroon Mumtaz for making available their global uncertainty estimates. We further thank Stefan Neuwirth and Roberto Golinelli for providing us with historic German and Italian GDP real time data.

[†]Center for Advanced Studies, EURAC Research, Drususallee 1, I-39100 Bozen, andreas.dibiasi@eurac.edu

[‡]KOF Swiss Economic Institute, ETH Zurich, Leonhardstrasse 21, CH-8092 Zurich, sarferaz@kof.ethz.ch

1 Introduction

In times of economic crisis measuring macroeconomic uncertainty and understanding its various effects on the economy are essential to an efficient and adequate response of policy makers. To further our understanding of these effects, it appears promising to investigate the cross-country variation in the relationship between uncertainty and economic activity. However, such a cross-country analysis requires a set of internationally comparable measures of macroeconomic uncertainty, constituting a challenging and data intensive task.¹

This paper constructs measures of macroeconomic uncertainty that are defined as the conditional volatility of an unpredictable forecast as in, e.g., Jurado et al. (2015) and that are available for a large set of countries. To obtain this goal, we draw on the macroeconomic data revisions literature, thereby treating statistical agencies' estimates of first releases of macroeconomic variables as forecasting exercises and their subsequent revisions as forecast errors.² We extract the unpredictable part of data revisions by decomposing them into news – the error from an unpredictable rational forecast – and noise, which is defined as a classical errors-in-variables. Specifically, we follow the approach of Jacobs and van Norden (2011) in modeling data revisions with news and noise, enriching it with stochastic volatility components. Our measure of macroeconomic uncertainty is thus defined as the conditional volatility of the error corresponding to the unpredictable part of those data revisions. It is important to note that these estimates of macroeconomic uncertainty are consistent across OECD countries, given the nature of standardized national accounting procedures.³ Note also that in constructing coherent macroeconomic variables statistical

¹See Redl (2018) for a recent attempt of producing objective measure of macroeconomic uncertainty for different countries, depicting the tedious data intensive nature of this approach. See also Mumtaz and Theodoridis (2017), Carriero et al. (2019) and Berger et al. (2017) for objective measures of uncertainty with a focus on extracting global uncertainty. Moreover, see Bloom (2014) for an overview article on challenges in measuring uncertainty.

²See Croushore and Stark (2001) for the construction of real-time data sets and their relevance for macroeconomic research.

³Statistical agencies in OECD countries follow similar national accounting standards. The data provided by the OECD database is based on the 2008 System of National Account. See also the website of the OECD for an overview of national legislation insuring the implementation of international accounting standards (<http://www.oecd.org/sdd/na/implementingthesystemofnationalaccount2008.htm>).

agencies take into account a plethora of series that include a huge amount of sensitive data partly only available to the statistical agency. Thus, in contrast to the bottom-up approach of, e.g., Jurado et al. (2015), we follow a top-down approach, where we partly outsource the information acquisition to the statistical agency.

As a second main contribution, we use our newly created international set of indicators to investigate the role of labor adjustment costs in transmitting uncertainty shocks. We subdivide the countries into high employment protection legislation (EPL) countries and low employment protection legislation countries using the OECD Employment Protection Database. In an 8-variable VAR analysis that uses data from 1988Q1 to 2016Q3, we find that the degree of labor protection plays a crucial role in the propagation of uncertainty shocks. Uncertainty shocks hurt the economy in countries with stricter employment protection legislation less than in countries with low labor protection standards. To learn more about the role played by EPL in the propagation mechanism of uncertainty shocks, we employ the theoretical model of Bloom et al. (2018). Within their framework, our focus is on the effects of changes in firing costs, assuming that stricter employment protection legislation hinder firms to lay off employees and thus lead to higher firing costs. In a first step, we calibrate, solve, and simulate the model of Bloom et al. (2018) twice, once for an economy for low EPL and once for an economy with high EPL. We then use the two calibrated models to simulate the reaction of the economy to an imposed uncertainty shock. According to the theoretical model and in line with our empirical findings, an uncertainty shock has less deteriorating effects in an economy with high EPL than in one with low EPL.

Our other contribution to the objective uncertainty literature is that we use real-time data and thus compute forecast errors at time t given information available to the economic agents up to and including at time t . Forecast errors in the objective uncertainty literature are usually computed using the most recent vintage of macroeconomic variables including information that go beyond time t . Limiting our estimations to information that economic agents had about aggregate variables at time t is in line with the above mentioned definition of macroeconomic uncertainty and might have important implications. For instance, up to the first oil price shock in the early 1970s, economic agents might not have been aware of the importance of the oil price for the economy as the data

prior to the oil price shock were uninformative about this relationship. Thus, forecast errors during the 1970s recessions are different if one trains a forecasting model with data up to that point in time or uses information that go beyond the 1970s.

This paper also contributes to the data revisions literature by extending the news and noise model of Jacobs and van Norden (2011) in two dimensions. First and as mentioned earlier, we setup a procedure that allows the error variances of the Jacobs and van Norden (2011) model to vary over time, by adding stochastic volatility components into their framework. Second, we show how to cope with so called benchmark revisions, which happen less frequently than usual revisions and are due to changes in the definition or structure of variables. These benchmark revisions usually change the whole history of the vintage, making them challenging to work with. To cope with these benchmark revisions, we assume that they change the stochastic properties of the underlying true value of the variable of interest, which we capture by means of time-varying coefficients.

We apply our procedure to a post WWII real-time dataset collected for 39 countries, deriving an international set of estimates of macroeconomic uncertainty. For the U.S., our measure pinpoints periods of highest uncertainty during the mid-1970s, beginning of 1980s, beginning of 2000s and during the recent great financial crisis, which is qualitatively consistent with other measures of U.S. uncertainty. However, our measure already peaks in the mid-1970s, highlighting the turmoils during the 1970s. We also construct a global uncertainty measure by using a GDP weighted average of all country specific uncertainty indicators. According to our measure of global uncertainty, the period during the mid-1970s and the great financial crisis stand out in terms of uncertainty, which is in line with most of the measures of global uncertainty.⁴ We also perform a VAR analysis for the U.S. and the G7 countries. The impulse response functions computed for the U.S. are very similar to impulse responses from a VAR including the uncertainty indicator of Jurado et al. (2015). These impulse response functions are qualitatively confirmed by the impulse responses estimated for an aggregate of the G7 countries.

The remainder of the paper is structured as follows: In Section 2, we discuss the empirical

⁴We compare our measure of uncertainty with the global uncertainty indicators presented in Mumtaz and Theodoridis (2017), Redl (2018), Carriero et al. (2019) and Berger et al. (2017).

framework and the estimation procedure. Section 3 discusses the construction of the real-time data set that serves as the basis for the uncertainty indicator. Section 4 and 5 present the uncertainty indicators and evaluate the macroeconomic relevance of uncertainty shocks. Section 6 examines the role of labor adjustment costs in the propagation of uncertainty shocks and Section 7 concludes.

2 Econometric Framework

In this section, we describe our econometric model, show how to derive direct measures of macroeconomic uncertainty, and how we cope with benchmark revisions. Finally, we briefly discuss our estimation procedure.

We follow the standard notation in the data revision literature where y_t^{t+j} denotes an estimate published at time $t + j$ of some real-valued scalar variable y at time t for $t = 1, \dots, T$ and $j = 1, \dots, L$. According to Jacobs and van Norden (2011) the j th release of y can be expressed as a function of its “true” value and a measurement error that is decomposed into a news and a noise term

$$y_t^{t+j} = \tilde{y}_t + \nu_t^{t+j} + \zeta_t^{t+j}, \quad (1)$$

where \tilde{y}_t represents the true value, ν_t^{t+j} the news component and ζ_t^{t+j} the noise component.⁵ Within this setup the noise component is interpreted as classical errors-in-variables and the news component as a rational forecast error.⁶ The main assumptions to distinguish between news and noise innovations are their correlation with the underlying true value of the variable. It is thus assumed that the news component carries information about the “true” value of the variable (i.e. $E[\tilde{y}_t, \nu_t^{t+j}] \neq 0$), whereas the noise components are independent of the “true” value of the variable (i.e., $E[\tilde{y}_t, \zeta_t^{t+j}] = 0$), with $E[\nu_t^{t+j}, \zeta_t^{t+j}] = 0$ for all t and j .

⁵See Kishor and Koenig (2012) for another framework that allows the estimation of both news and noise type measurement errors in data revisions. See Jacobs and van Norden (2011) for a more detailed discussion of the data revision literature.

⁶See Mankiw et al. (1984), Mankiw and Shapiro (1986) and de Jong (1987), where measurement errors are described as news. See Sargent (1989) for a statistical agency that estimates the “true” value making full use of available information and thus resulting into unpredictable revisions.

To estimate those news and noise components, we build on the state space model developed by Jacobs and van Norden (2011), which can be expressed as

$$Y_t = Z\alpha_t, \quad (2)$$

$$\alpha_t = \varphi + T\alpha_{t-1} + R\eta_t, \quad (3)$$

where

$$Y_t = \begin{bmatrix} y_t^{t+1} \\ y_t^{t+L} \end{bmatrix}, Z = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix}, \alpha_t = \begin{bmatrix} \tilde{y}_t \\ \nu_t \\ \zeta_t^{t+1} \\ \zeta_t^{t+L} \end{bmatrix},$$

$$\varphi = \begin{bmatrix} c \\ 0 \\ 0 \\ 0 \end{bmatrix}, T = \begin{bmatrix} \rho & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, R = \begin{bmatrix} \sigma^y & \sigma^\nu & 0 & 0 \\ 0 & -\sigma^\nu & 0 & 0 \\ 0 & 0 & \sigma^{\zeta 1} & 0 \\ 0 & 0 & 0 & \sigma^{\zeta L} \end{bmatrix}, \eta_t = \begin{bmatrix} \eta_t^y \\ \eta_t^\nu \\ \eta_t^{\zeta 1} \\ \eta_t^{\zeta L} \end{bmatrix}$$

with $\eta_t \sim N(0, I_4)$, where c and ρ are coefficients and σ^i represents the standard deviation of η_t^i for $i = \tilde{y}, \nu, \zeta 1, \zeta L$.

2.1 Estimating Macroeconomic Uncertainty

To obtain direct estimates of macroeconomic uncertainty, we define economic uncertainty similar to Jurado et al. (2015) as the conditional volatility of the unpredictable part of future values of the variable, i.e. in our case of subsequent releases of the variable. We thus treat the estimation procedure of early releases as a forecasting exercise. Within this context, the news components can then be seen as the unpredictable part of the forecast error. We obtain estimates of macroeconomic uncertainty by estimating changes in the variance of the news component. To do this we enrich the Jacobs and van Norden (2011) model with stochastic volatility components, modifying Equation (3) to

$$\alpha_t = \varphi + T\alpha_{t-1} + R_t\eta_t, \quad (4)$$

where

$$R_t = \begin{bmatrix} \sigma_t^y & \sigma_t^\nu & 0 & 0 \\ 0 & -\sigma_t^\nu & 0 & 0 \\ 0 & 0 & \sigma_t^{\zeta 1} & 0 \\ 0 & 0 & 0 & \sigma_t^{\zeta L} \end{bmatrix}$$

with $\sigma_t^i = \exp(h_t^i)^{1/2}$ for $i = \tilde{y}, \nu, \zeta 1, \zeta L$ and α_t, φ, T and η_t specified as in (3). The volatility components are modelled as latent variables whose logarithms are assumed to follow independent AR(1) processes:

$$h_t^i = \mu^i + \phi^i(h_{t-1}^i - \mu^i) + \tau^i \epsilon_t^i, \quad (5)$$

where μ^i, ϕ^i, τ^i are parameters, $\epsilon_t^i \sim N(0, 1)$ and $i = \tilde{y}, \nu, \zeta 1, \zeta L$.⁷

Our measure of macroeconomic uncertainty at time t can thus be expressed as

$$U_t \equiv \sigma_t^y + \sigma_t^\nu,$$

which is a combination of the conditional volatility of the underlying true value and the conditional volatility of the rational forecast error, i.e. news.

2.2 The Case of Benchmark Revisions

When working with real-time data the nature of data revisions is of paramount importance. Usually revisions occur at regular basis, reaching back 2-3 years within the particular vintage. There are however also revisions that happen less frequently and are due to, for example, changes in the definition of a variable. These so called benchmark revisions usually change the whole history of the vintage, which makes them difficult to cope with.

In this paper we tackle this issue by assuming that benchmark revision occur potentially at any point in time and that they change the nature of the variable itself. More specifically, we assume that they cause a change in the stochastic properties of the “true” value \tilde{y}_t . We capture this change by allowing the coefficients in the equation of \tilde{y}_t to vary over time, modifying Equation (4) to:

$$\alpha_t = \varphi_t + T_t \alpha_{t-1} + R_t \eta_t, \quad (6)$$

where

$$\varphi_t = \begin{bmatrix} c_t \\ 0 \\ 0 \\ 0 \end{bmatrix}, T_t = \begin{bmatrix} \rho_t & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (7)$$

⁷See, e.g., Kim et al. (1998).

and

$$\begin{bmatrix} c_t \\ \rho_t \end{bmatrix} = \begin{bmatrix} c_{t-1} \\ \rho_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t^c \\ \epsilon_t^\rho \end{bmatrix}$$

with $[\epsilon_t^c \ \epsilon_t^\rho]' \sim N(0, V)$ and α_t , R_t and η_t specified as in (4).

2.3 Priors

We use priors that are as diffuse as possible. The prior on V is assumed to follow an Inverse Wishart distribution. The shape parameter is set to 3. The prior for the scale parameter is optimized according to the length of the series, in order for the AR(1) to cover the range of possible values. The prior for the variance of the stochastic volatilities is assumed to follow an Inverse Gamma distribution. We set the priors on the variance of the stochastic volatilities as uninformative as possible.

2.4 Estimation Procedure

We obtain draws from the posterior of our model's parameters using Markov Chain Monte Carlo methods. More specifically, we use Gibbs sampling.⁸ The Gibbs sampler consists of the following blocks:

1. Draw α_t conditional on φ_t , T_t , R_t and data Y_t using a forward filtering backward sampling as described in, e.g., Carter and Kohn (1994),
2. Draw h_t^i , μ^i , ϕ^i , τ^i for $i = \tilde{y}, \nu, \zeta 1, \zeta L$ conditional on α_t , φ_t , T_t using the ancillarity-sufficiency interweaving approach proposed by Kastner and Frühwirth-Schnatter (2014),
3. Draw φ_t and T_t conditional on α_t and R_t using the simulation smoothing approach introduced by McCausland et al. (2011).
4. Draw V conditional on α_t , R_t , φ_t , T_t from an Inverse Wishart distribution.

See Appendix A for a more detailed discussion of our estimation procedure.

⁸The Gibbs sampling procedure was programmed in Julia and is available upon request.

3 Real-Time Data

We use data revisions in real GDP for 39 countries to construct the uncertainty indicator. In order to obtain a comprehensive data set for various countries, we need to tap and combine several data sources. The largest part of our data is provided by the *Original Release Data and Revisions Database*. The *Original Release Data and Revisions Database* is part of OECD Main Economic Indicators database (OECD, 2017) and represents the central data source of this project. The database provides different releases of macroeconomic aggregates for many countries. This study uses data from 39 countries. Table 1 provides an overview of the countries included in our study, the data provider and the first available data point. Unfortunately, the *Original Release Data and Revisions Database* provides releases of macroeconomic variables only since 1999. For data prior to 1999, we need to rely on other data provider. We primarily use the data made available by the Federal Reserve Bank of Dallas for releases prior to 1999. Fernandez et al. (2011) collect real-time data for various economies including those that we use in this study. The authors assemble the dataset from original quarterly releases of different macroeconomic aggregates from 1962 to 1998. We currently use these data for all countries except the U.S., Germany, Italy, Australia and New Zealand. For the U.S., we use data provided by the Federal Reserve of Philadelphia as they provide more exhaustive data compared to the data provided by Federal Reserve of Dallas. For Germany we rely on data provided by Boysen-Hogrefe and Neuwirth (2012) and for Australia we use data provided by the Australian Real-Time Macroeconomic Database (Lee et al., 2012). For New Zealand we use data provided by the Reserve Bank of New Zealand (Sleeman, 2006) and for Italy, we also use data releases of ISTAT that were kindly provided by Golinelli and Parigi (2008).⁹

⁹Appendix B describes these various data sources and outlines the construction of our data base in more detail. We will provide the final real-time dataset as well as the code to construct it upon request.

Table 1: Data Source of Uncertainty Indicators

Countries	MEI Code	Datasource prior to 1999	Available since
Australia	AUS	Real-Time Macroeconomic Database (U. Melbourne)	1967 Q3
Austria	AUT	FED Dallas	1999 Q3
Belgium	BEL	no data	1999 Q1
Brazil	BRA	no data	2000 Q2
Canada	CAN	FED Dallas & Bank of Canada	1961 Q3
Chile	CHL	no data	2010 Q1
Czech Republic	CZE	no data	1999 Q1
Denmark	DNK	FED Dallas	1993 Q2
Estonia	EST	no data	2010 Q3
Finland	FIN	FED Dallas	1993 Q4
France	FRA	FED Dallas	1987 Q2
Germany	DEU	FED Dallas & Boysen-Hogrefe and Neuwirth (2012)	1964 Q4
Great Britain	GBR	FED Dallas	1964 Q4
Hungary	HUN	no data	2002 Q2
Greece	GRC	no data	2003 Q4
Iceland	ISL	no data	2002 Q4
India	IND	no data	2005 Q4
Indonesia	IDN	no data	2005 Q4
Ireland	IRL	no data	2002 Q2
Israel	ISR	no data	2010 Q2
Italy	ITA	FED Dallas & Golinelli and Parigi (2008)	1974 Q3
Japan	JPN	FED Dallas	1964 Q3
Korea	KOR	FED Dallas	1996 Q4
Luxembourg	LUX	no data	2004 Q4
Mexico	MEX	FED Dallas	1994 Q2
Netherlands	NLD	FED Dallas	1993 Q3
New Zealand	NZL	Reserve Bank of New Zealand	1994 Q4
Norway	NOR	FED Dallas	1993 Q3
Poland	POL	no data	2002 Q2
Portugal	PRT	FED Dallas	1992 Q3
Russia	RUS	no data	1999 Q3
Slovakia	SVK	no data	2000 Q3
Slovenia	SVN	no data	2010 Q1
South Africa	RUS	no data	2001 Q4
Spain	ESP	FED Dallas	1993 Q1
Sweden	SWE	FED Dallas	1989 Q4
Switzerland	CHE	FED Dallas	1987 Q2
Turkey	TUR	FED Dallas	1993 Q1
USA	USA	FED Philadelphia	1961 Q4

Notes: Central data source is the *Original Release Data and Revisions Database*. The column *Countries* depicts the country and *MEI Code* the country code from the *Original Release Data and Revisions Database*. The column *Datasource prior to 1999* describes the data source of releases prior to 1999. The column *Available since* states beginning of a country's uncertainty indicator. Rows in green highlight countries with data available prior to 1990Q1, rows in gray depict countries with data from 1990Q1 to 2000Q4 and rows in red represent countries with data available only from 2001Q1 onward.

While data availability fluctuates a lot between countries, we have surprisingly long time series for many countries. For 10 countries we have real-time data for more than 30 years (green shaded countries) and for another 16 countries we have more than 20 years of data (gray shaded countries). For four countries only, we have less than 10 years data. Besides data availability, also the average revisions change heavily between single countries. While large countries in terms of GDP, such as the U.S., France, Germany, Canada and Australia tend to have small revisions, smaller countries, including Ireland, Island and Luxembourg, appear to have much larger revisions. Figure 1 visualizes the distribution of the 10th revision of year-over-year growth rates of real GDP for different countries.

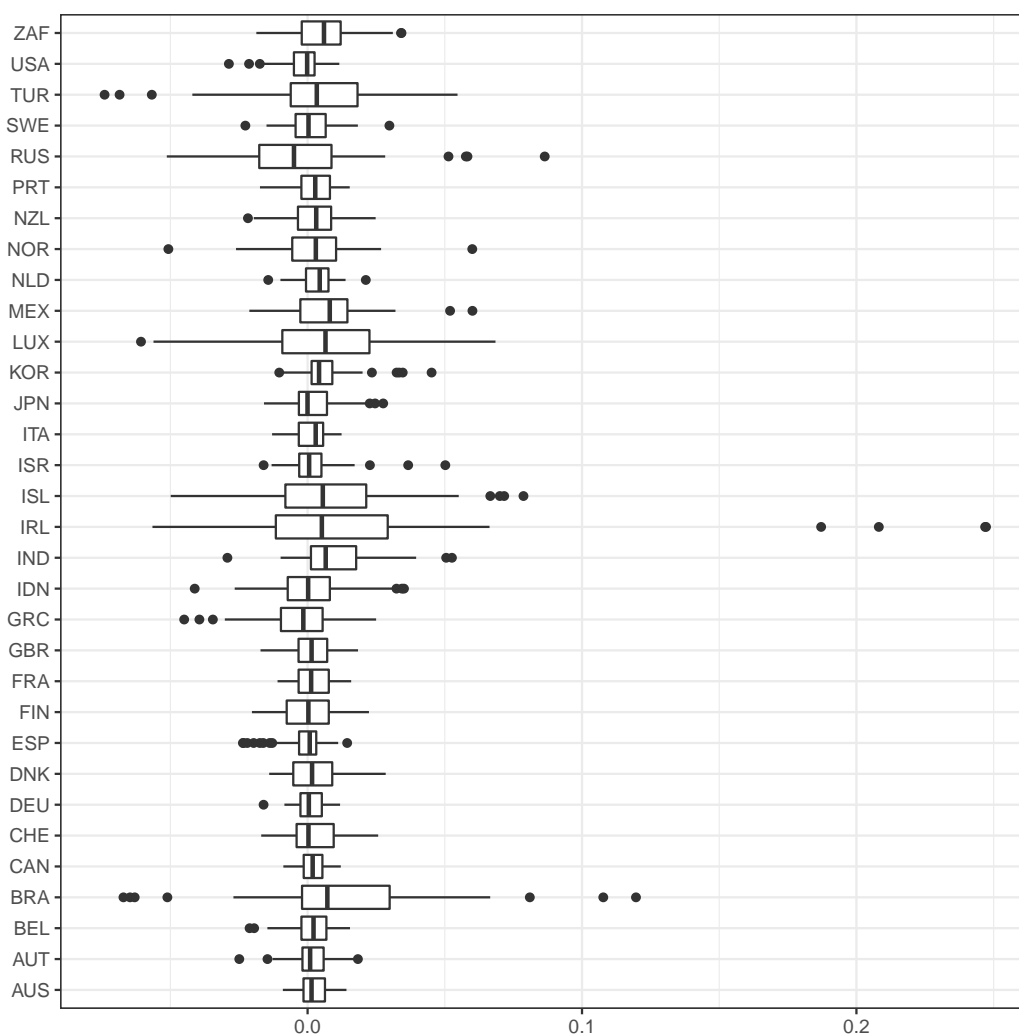


Figure 1: Boxplot of the 10th revision for the periods from 2000 Q1 onward.

Most countries reveal a statistically significant upward revision of their growth rates over time. The 10th release of GDP growth tends on average to be larger than the first release. Only four countries including the U.S., Russia, Greece and Spain, report on average a lower growth rate at the 10th release than on the first release.¹⁰

4 Estimates of Macroeconomic Uncertainty

Using the econometric framework outlined in Section 2 and the real-time dataset described in Section 3, we obtain estimates of macroeconomic uncertainty for 39 countries.¹¹ We now present and discuss the resulting uncertainty measures. Thereby, we focus on uncertainty in the United States and global uncertainty.

Our methodical framework provides macroeconomic uncertainty estimates for the United States that are similar to existing uncertainty measures. Figure 2 presents our revision-based uncertainty measure for the U.S. (blue solid line) and compares it to existing proxies found in the literature. These alternative measures include the macroeconomic uncertainty indicator proposed by Jurado et al. (2015) (green solid line), the economic policy uncertainty index developed by Baker et al. (2016) (ochre dashed line) and the VIX (purple dashed line), a popular uncertainty indicator that reflects market's expectation of volatility implied by the S&P 500 index options.

Our data revision based indicator reaches its highest levels during the recession in the 70s that was characterized by the first oil price shock and the collapse of the Bretton Woods system and marked the end to the overall Post-World War II economic expansion. The Great Recession of 2008 marks the second highest peak of our indicator. The indicator further indicates times of heightened uncertainty during the '82 recession and at the beginning of the 2000s, during the dotcom bubble burst. Overall, our indicator resembles most the indicator proposed by Jurado et al. (2015)(henceforth JLN). However, while JLN peaks during the Iran Revolution in 1979, the revision based indicator reaches its highest levels during the 70s recession. Compared to other uncertainty measures, our uncertainty estimate for the U.S. displays a significantly lower volatility and indicates only

¹⁰See Figure 9 in Appendix B for a better overview of average revisions.

¹¹We provide all uncertainty indicators on our website.

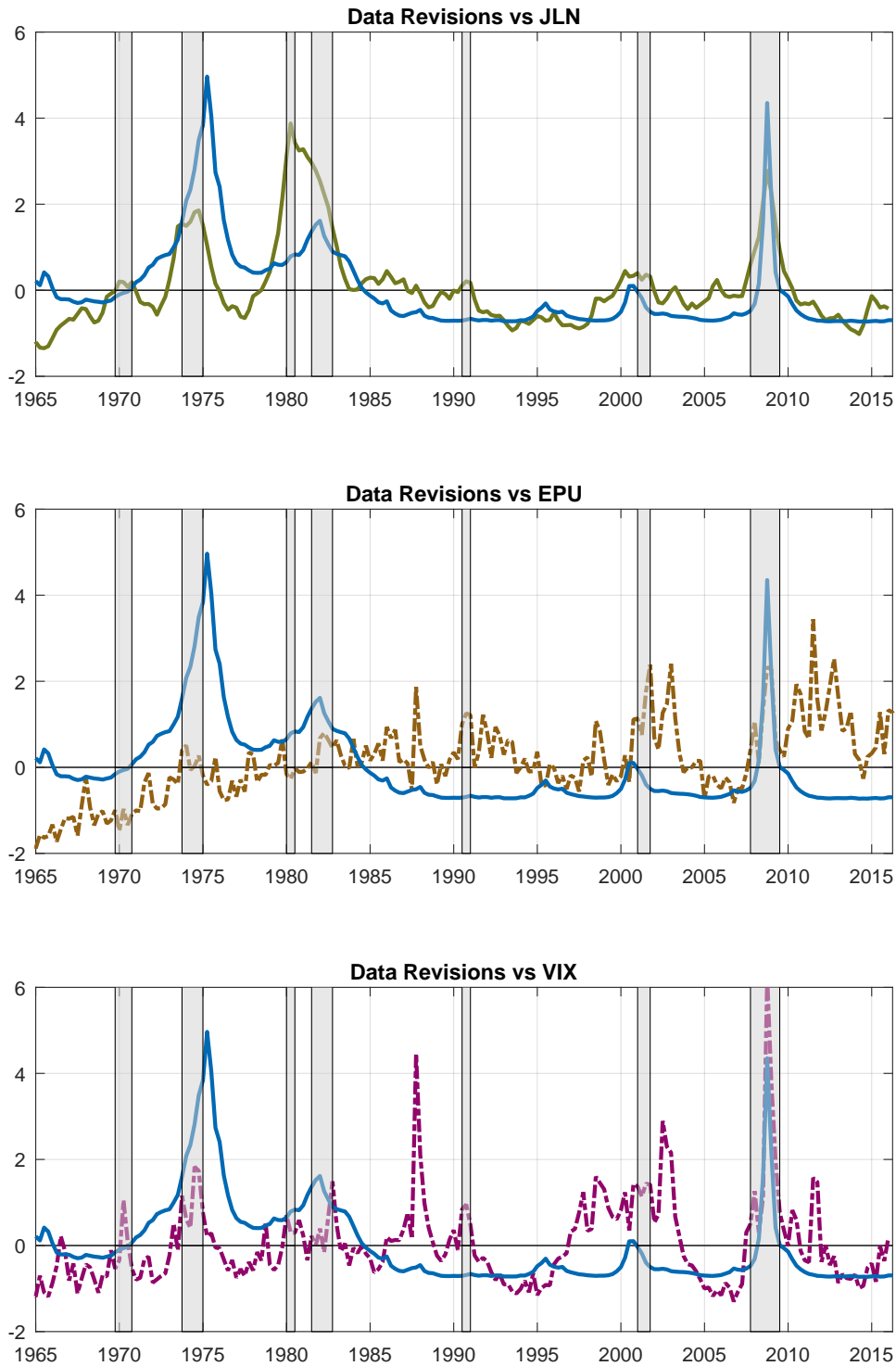


Figure 2: Uncertainty United States: Macroeconomic Uncertainty

Notes: This figure compares different uncertainty indicators for the United States from 1960Q1 to 2016Q3. In the first pane, the green solid line displays the indicator for macroeconomic uncertainty (quarterly averages, horizon 12, MacroFinanceRealUncertainty_2017Aug.update) developed by Jurado et al. (2015) and the blue solid line shows the newly proposed measure of macroeconomic uncertainty. In the second pane, the dashed ochre line shows quarterly average of the Economic Policy Indicator proposed by Baker et al. (2016). The last pane compares the VIX (realised volatility before 1989) to the new uncertainty measure. All indicators are demeaned and normalized to unit variance.

a few mayor uncertainty shocks during 1965 and 2016. For instance, while both the EPU and the VIX peak in 1987 as a result of the Black Monday, the revision based indicators hardly blinks. Similar, after the Great Recession of 2008, the EPU reaches all-time-high level of economic policy uncertainty. However, the economic policy uncertainty does not translate into macroeconomic uncertainty as both the revision based indicator as well as JLN return to very low level after the recession.

Although we obtain uncertainty estimates for 39 countries, for the sake of brevity, we abstain from discussing all countries in the main text and refer the reader to Appendix C for a presentation of all uncertainty indicators.¹² Instead, we use the comprehensive number of uncertainty indicators to examine uncertainty on a global level. We construct a global uncertainty measure as the weighted mean of single country indicators. We achieve this by first standardizing the uncertainty indicator of each country and then computing the weighted average by weighing each country according to its real GDP.¹³ The countries included in the construction of the global uncertainty indicator account for approximately 50% of world GDP during the first half of the sample. During the second half of the sample, the included countries account for more than 75% of world GDP. Figure 11 presents the global uncertainty indicators. From the 1960s to today, our estimates suggests two large global uncertainty shocks. The first occurred during the oil price shock in the 70s, the second global uncertainty shock was experienced during the Great Recession in 2008. The only other notable increase in global uncertainty occurred after the second oil price shock and the subsequent early 80s recession.

Recently, various papers started to measure and study uncertainty on a global dimension.¹⁴ While several papers propose measures of global economic policy uncertainty, world risk and global financial uncertainty, studies that attempt to measure global macroeconomic uncertainty are limited: Redl (2017) constructs a JLN based global uncertainty measure that is based on global macro and financial data from emerging and advanced economies. Mumtaz and Theodoridis (2017) (henceforth MT) use a factor model with stochastic volatility to decompose the time-varying variance of macroeconomic and fi-

¹²Figure 10 and Figure 11 in the Appendix present the uncertainty estimates of all countries.

¹³The global uncertainty indicator is based on an unbalanced sample. That is, countries' uncertainty estimates are considered according to their availability.

¹⁴See Castelnovo (2019) for a recent review on the literature focusing on global uncertainty.

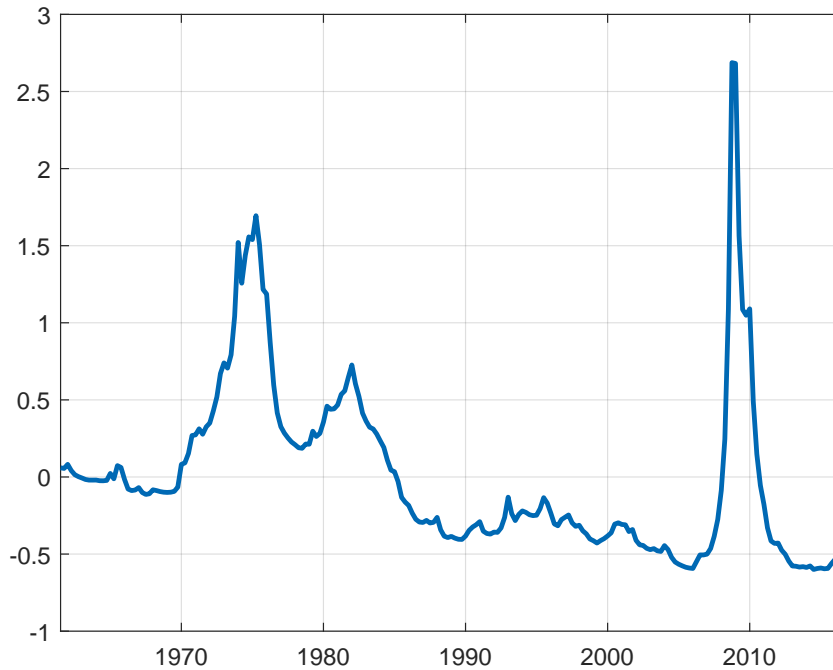


Figure 3: Global Uncertainty

Notes: This figure shows the weighted average of countries' normalized uncertainty measures. We weight single countries according to their real GDP. The shaded area displays the share of World GDP that is represented in the uncertainty indicator (right axis). While the included countries represent approximately half of world GDP during the first half of the sample, the economies included in the second half represent around 75% of total GDP.

nancial variables of eleven OECD countries¹⁵ into contributions from country-specific uncertainty and uncertainty common to all countries. Carriero et al. (2019) (henceforth CCM) estimate a large, heteroskedastic VAR on 19 industrialized economies to obtain estimates of global uncertainty. Berger et al. (2017) (henceforth BGK) use a dynamic factor model with stochastic volatility to identify the common component of macroeconomic uncertainty from 20 OECD countries. Figure 4 compares these indicators to our data-revision based indicator. While the data revision based indicator match the other indicators remarkably well, two differences stand out. First, similar to the indicator of the U.S., the data revision based indicator is the least volatile of all indicators. Second, while the other four indicators peak during the great recession of 2008 at 4 standard deviations or higher above their mean, the data revision indicator peaks at 2.5 standard deviations.

¹⁵These countries include United States, United Kingdom, Canada, Germany, France, Spain, Italy, Netherlands, Sweden, Japan and Australia.

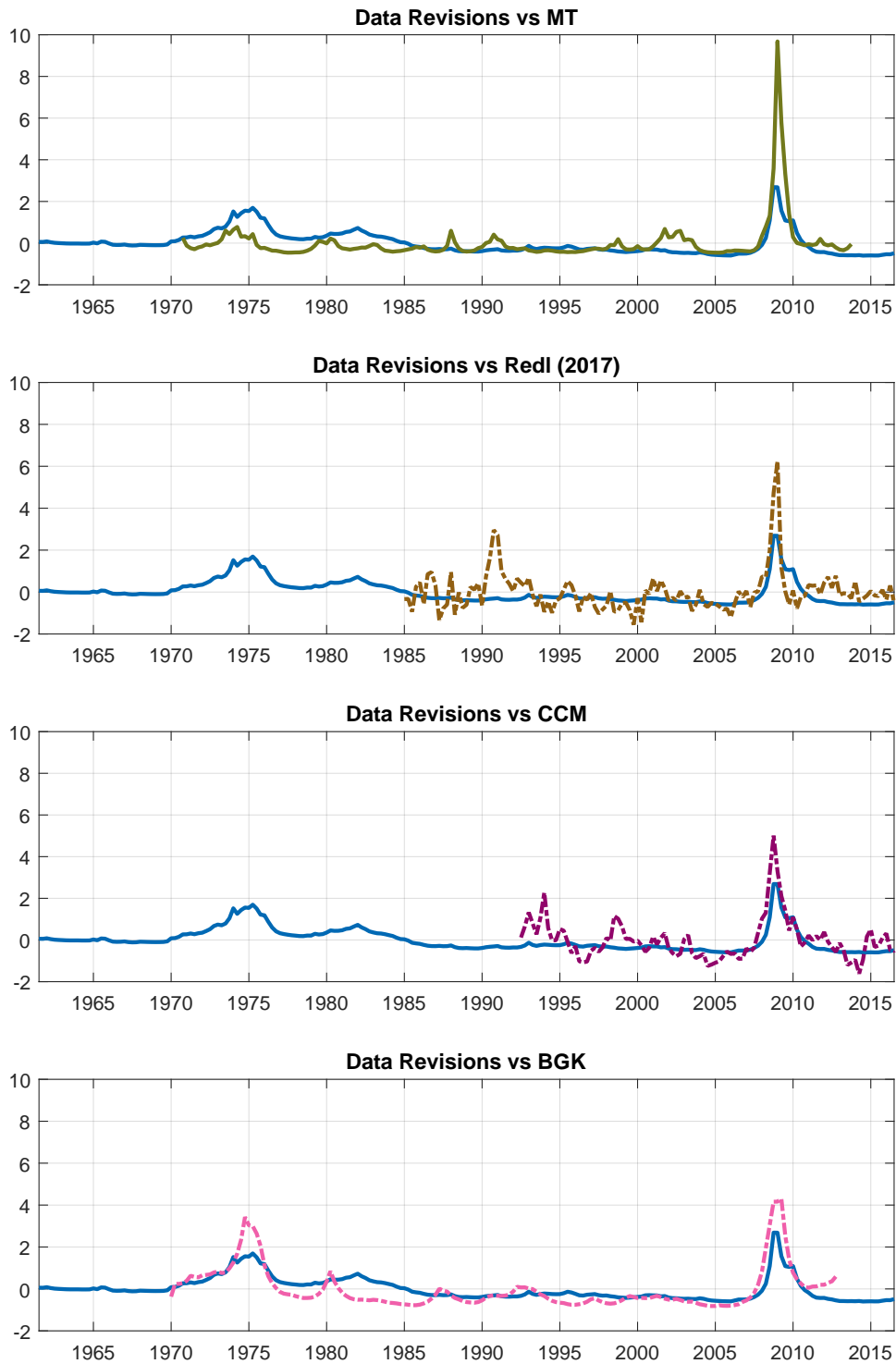


Figure 4: Global Macroeconomic Uncertainty

Notes: This figure compares different global macroeconomic uncertainty indicators. In the first pane, the green solid line displays the indicator for global macroeconomic uncertainty by Muntaz and Theodoridis (2017) and the blue solid line shows the data revision based indicator of global macroeconomic uncertainty. In the second pane, the dashed ochre line shows quarterly averages of the global macroeconomic uncertainty measure proposed by Redl (2018). The third pane compares the global uncertainty indicator by Carriero et al. (2019) to the new uncertainty measure. The last pane display the indicator proposed by Berger et al. (2017) together with the revision based indicator. All indicators are demeaned and normalized to unit variance.

5 Cross-Country Impact of Uncertainty Shocks

Following the existing empirical research on uncertainty, we use a VAR analysis to study the dynamic relationships between macroeconomic activity and uncertainty. We consider the following VAR model:

$$x_t = c_b + \sum_{i=1}^p B_i x_{t-i} + u_t, \quad (8)$$

where x_t is a $n \times 1$ vector containing all n endogenous variables, $t = 1, \dots, T$ denotes time, c_b is a $n \times 1$ vector of constants, B_i for $i = 1, \dots, p$ are $n \times n$ parameter matrices and u_t is the $n \times 1$ one-step ahead prediction error with $u_t \sim N(0, \Sigma)$, where Σ is the $n \times n$ variance-covariance matrix. The prediction error u_t can be written as a linear combination of structural innovations $u_t = A\epsilon_t$ with $\epsilon_t \sim N(0, I_n)$, where I_n is an $(n \times n)$ identity matrix and where A is a non-singular parameter matrix.

We choose a recursive identification scheme and a VAR similar to the one proposed in Basu and Bundick (2017), augmenting their VAR setup with a stock market index. Similar to Bloom (2009), we include the stock-market level as the first variable in the VAR. This ensures that the impact of the stock market is already considered for when evaluating the impact of uncertainty on the economy. The ordering of our VAR is as follows:

$$\text{VAR} - 8 \quad \begin{bmatrix} \textit{stock market} \\ \textit{uncertainty} \\ \textit{policy rate} \\ \textit{CPI} \\ \textit{employment} \\ \textit{investment} \\ \textit{consumption} \\ \textit{GDP} \end{bmatrix}. \quad (9)$$

We estimate the model using Bayesian methods, specifying diffuse priors.¹⁶ Similar to

¹⁶We consulted the Bayesian information criterion and the Akaike information criterion for choosing a lag length. For the different countries and the different criterion, the suggested lag-lengths varied from

Jurado et al. (2015), we use the posterior mean of our uncertainty indicator discussed in the Section 4 as a measure for macroeconomic uncertainty in our VAR. However, as a further robustness check, we have also estimated the VAR taking into account the uncertainty surrounding our uncertainty indicator. To incorporate the whole posterior distribution instead of just the posterior mean, we extend the algorithm in Section 2.4 by one further block. In this additional step, we obtain a draw for the VAR parameters from a Normal-Inverse Wishart distribution, conditional a draw simulated from the posterior of the uncertainty indicator. The resulting posterior distributions are summarized in Figures 13 and 14 in Appendix D.

5.1 Impact of Uncertainty Shock in the U.S.

We employ the described VAR to investigate the impulse responses functions of key macro variables to uncertainty shocks that are derived using our data revision based uncertainty measure. To validate our uncertainty measure, we compare the impulse responses obtained using the data revisions based uncertainty measure to impulse response functions that are computed with the macroeconomic uncertainty index by Jurado et al. (2015). The estimation sample spans the period 1982Q1–2016Q3.¹⁷

Figure 5 reports the impulse responses of GDP, investment, employment and consumption to an uncertainty shock in the United States. A one standard deviation shock in uncertainty has an adverse and enduring effect on all macroeconomic variables (blue dashed line). For most of the variables the drop lasts for about two years, with most of posterior probability mass lying below zero. During this period output declines by around 0.4%, investment by 1% and employment by about 0.5%. The recovery from the uncertainty shock takes up to 10 years and more. While these effects seems somewhat strong and long-lasting, they are very similar to the uncertainty measure of Jurado et al. (2015) (green line).

$p = 1$ to $p = 3$. We set the length to $p = 2$ throughout this paper. The principal findings of the paper do not change when using lag length $p = 3$ instead.

¹⁷Due to irregularities in the revision scheme of U.S. GDP during the 1970s, we start the VAR analysis in 1982Q1 and not earlier. See Table 2 in Fernandez et al. (2011) for a more detailed discussion of these irregularities.

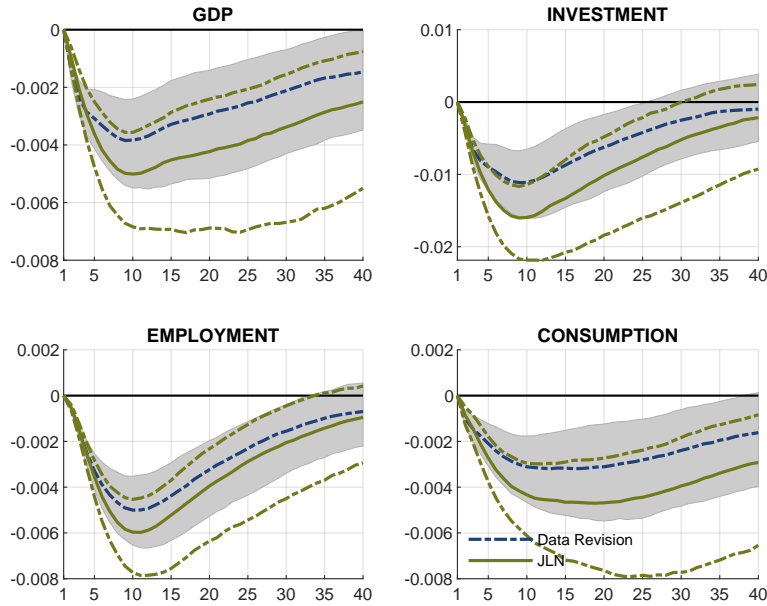


Figure 5: Impulse responses to an uncertainty shock in the U.S.

Notes: The dotted blue line depicts the posterior mean and the grey shaded area the 68% error bands for the impulse responses to an one standard deviation uncertainty shock computed from a VAR model including the uncertainty measure based on data revisions. The solid green line depicts the posterior mean with the dotted green lines representing the 68% error bands for the impulse responses from a model that uses the uncertainty measure of Jurado et al. (2015). The estimation sample spans the period 1982Q1–2016Q3.

5.2 Impact of Uncertainty Shock in G7 countries

In this section, we examine the effects of uncertainty shocks within an international context. Thereby, we use a subset of the uncertainty indicators discussed in Section 4 to estimate the VAR model outlined above for the G7 countries. The intergovernmental economic organization comprises Canada, France, Germany, Italy, Japan, United Kingdom and the United States. In terms of economic importance, the organization makes up for about one third of global GDP based on purchasing power parity. We estimate the VAR jointly allowing for country-specific parameters. To obtain an aggregate impulse response for the G7 countries we average across country-specific impulse responses. Due to data limitations, we confine our estimates the sample from 1988Q1 to 2016Q3 for all countries.

Figure 6 shows the cross-country average impulse responses of GDP, investment, employment and consumption to an uncertainty shock. All variables unveil a negative relationship with uncertainty. While the impulse responses for the G7 aggregate in Figure 6 are

qualitatively similar to the impulse responses obtained for the United States reported in Figure 5, the average G7 effect of uncertainty shock is about half as strong as the one found for the United States.

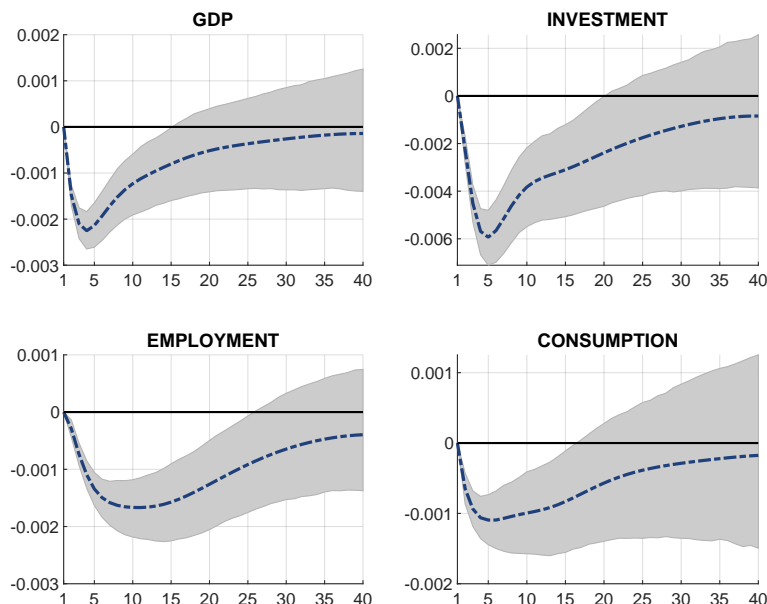


Figure 6: Impulse responses to an uncertainty shock for the group of G7 countries

Notes: The dotted blue line depicts the posterior mean and the grey shaded area the 68% error bands for the impulse responses to an one standard deviation uncertainty shock. The estimation sample spans the period 1988Q1–2016Q3.

6 On the Role of Employment Protection Legislation

While the relationship between capital adjustment costs and uncertainty has been extensively studied in the literature, relatively few studies focus on labor markets rigidities as a possible transmission channel of uncertainty to the real economy. Recently, however, scholars started to explore this channel in more detail. Cacciatore and Ravenna (2015) show that binding downward rigidity of wages reinforce the negative effects of uncertainty on employment. In a similar fashion, Leduc and Liu (2016) claim that nominal rigidities amplify the option-value channel through which uncertainty transmits the economy. Guglielminetti (2016) shows that firms reduce open vacancies when uncertainty increases in order to avoid expensive search activities and highlights its importance for the trans-

mission of uncertainty shocks. In this study, we focus on the role of firing costs as a possible transmission mechanism of uncertainty shocks. We proxy firing costs with the degree of employment protection legislation and argue that stricter employment protection makes it more difficult—and thus more costly—to fire employees.

To obtain a better understanding of the role of employment protection legislation (EPL) in the propagation of uncertainty shocks, we first study the role of EPL within a theoretical framework and, in a second step, we use our newly developed uncertainty measures to empirically test the theoretical predictions.

6.1 Theoretical Model

To study the importance of EPL for uncertainty shocks within a theoretical model, we need a model that features uncertainty shocks and allows us to impose a stricter EPL. The dynamic stochastic general equilibrium model proposed by Bloom et al. (2018) includes all necessary features. The real business cycle model considers an economy with identical households wanting to maximize life-time discounted utility. All households choose how much they want to consume, work and invest in order to maximize their life-time utilities. Furthermore, the model features an economy with heterogeneous firms that use labor and capital to produce a final good with the objective to maximize the life-time discounted value of their firm. Firms are subject to an exogenous process of productivity that has a firm-level and a macroeconomic component. Both the macroeconomic as well as the idiosyncratic productivity process varies in the first and second moment, with changes in second moment representing changes in uncertainty. Firms react to changes in productivity by adjusting capital and labor. However, adjusting capital and labor comes at a cost that firms have to take into account when maximizing their firm value.

We chose the model by Bloom et al. (2018) because of the exhaustive way to model capital and labor adjustment costs. In our case, we are particularly interested in the way the authors model labor adjustment costs. The model includes two types of labor adjustment costs (AC^n). Firms face fixed and linear costs when adjusting labor. Fixed costs represent a lump sum cost that arises when employees are hired or fired. This cost does not depend on the size of the adjustment but on the state of the economy. One can think these costs as arising from the deficiency in production owing to an experienced

employee leaving the company or a new employee entering it. In contrast to fixed costs, linear costs depend on the size of the labor adjustment. These costs include, among others, recruiting and training costs for new employees and severance payment when laying off employees. Labor adjustment costs can thus be formally expressed as

$$AC^n = \mathbb{1}(|s| > 0)y(z, A, k, n)C_L^F + \mathbb{1}(s > 0)C_H^P w + \mathbb{1}(s < 0)C_F^P w, \quad (10)$$

where C_L^F represent fixed labor adjustment costs that depends of the current state of production $y(z, A, k, n)$. C_H^P and C_F^P represent hiring and firing costs as a percentage of the annual wage bill w .

As we aim to examine the effects of stricter employment protection legislation, we adjust the parameter that we associate most with stronger labor protection: firing costs. Stricter employment protection legislation makes it harder for firms to lay off employees. Hence, stricter employment protection legislation increases firing costs. Theoretically, firing costs change the effects of uncertainty on employment in two ways. First, an increase in firing costs reduces firing when uncertainty increases. Second, an increase in firing costs reduces hiring. The reason for this is the following: In the presence of non-convex adjustment costs firms face Ss hiring policy rules (Scarf, 1959). That is, firms do not hire new employees until productivity reaches an upper threshold (the S in Ss) and do not fire until productivity hits a lower threshold (the s in Ss). Stricter employment protection legislation reduces the lower threshold. Hence, productivity needs to fall more before firms start firing employees. Overall employment will fall less compared to an economy with lower employment protection standards. This mechanism is similar to the one described by Bell (2016). Using a partial equilibrium model, the author shows that an increase in firing costs has a negative effect on employment because firms reduce hiring due to precautionary reasons. Overall, however, the negative effect on uncertainty is reversed as the increase in costs discourages firing by more than it does hiring.

In order to examine the role of EPL we calibrate, solve and simulate the model of Bloom et al. (2018) twice, once for an economy for low EPL and once for an economy with high EPL. In order to ensure comparability with Bloom et al. (2018) and the RBC literature in general, we do not change the calibration proposed by Bloom et al. (2018), except for the firing cost parameter. The literature on firing costs reports estimates that vary

considerably between countries. For the United States, Bloom et al. (2018) assume firing costs to be on average 1.8% of an annual wage bill. For continental European economies—countries that according to the OECD Employment Protection Database have on average stricter EPL—studies report substantially higher firing costs (Grund, 2006; Kramarz and Michaud, 2010). For illustrative purposes, we simply assume firing costs to be twice as high as in the case of Bloom et al. (2018), i.e. we assume firing costs to be on average 3.6% of an annual wage bill. Table 2 summarizes the labor adjustment parameters.

Parameter Description	Low EPL	High EPL
C_L^F : fixed hiring/firing costs (% sales)	0.021	0.021
C_H^P : per capita hiring (% of annual wage bill)	0.018	0.018
C_F^P : per capita firing cost (% of annual wage bill)	0.018	0.036

Table 2: Model Calibration

Notes: This table presents the model calibration and parameter choices. The calibration reflects a quarterly calibration of the model and is based on Bloom et al. (2018).

We use two calibrated models to simulate the reaction of the economy to an imposed uncertainty shock. In this case, an uncertainty shock corresponds to an increase in variance of the shock distribution from which future realisations of productivity will be drawn. Figure 7 presents the impulse responses of output, investment, employment and consumption to an uncertainty shock. The blue lines presents the impulse response to uncertainty shock under low employment protection legislation and the gray line shows the impulse response of the same uncertainty shock under high employment protection. According to the model, an uncertainty shock has less deteriorating effects on an economy with high employment protection legislation.

6.2 Evidence from a VAR

Now, we use the international set of revision based measures of uncertainty to test this theoretical prediction. We thus split countries into two groups according to their strictness of employment protection.¹⁸ To split countries according to their degree of employ-

¹⁸We confine this analysis to countries for which data since 1990. Hence, we end up with the United States, Canada, United Kingdom, Switzerland, Japan, France, Germany, Sweden and Italy.

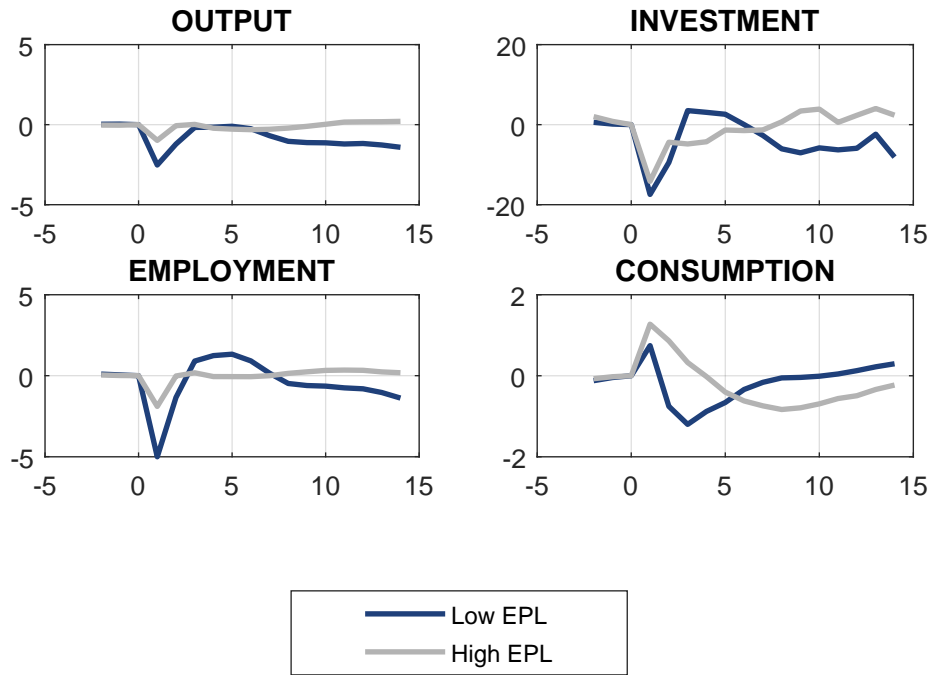


Figure 7: Uncertainty Shocks under high and low labor protection

Notes: This figure presents DSGE impulse responses of output, investment, employment and consumption after an uncertainty shock. Thereby, the blue lines presents the impulse response to uncertainty shock under low employment protection legislation and the gray line shows the impulse response of the same uncertainty shock under high employment protection.

ment protection, we use the annual time series data of the OECD Employment Protection Database to calculate the average value of the strictness of employment protection. Specifically, we use the measure of individual and collective dismissals (EPRC_V1) from 1985 to 2013. Table 3 ranks countries according to the strictness of employment protection.

The groups selected in Table 3 mirror our expectations with Anglo-Saxon economies displaying a low degree and continental European countries showing higher degree of employment protection standards. According to OECD Employment Protection Database, Switzerland and Japan have a very similar degree of EPL. In our baseline specification, we include Switzerland in the group with low labor protection and Japan in the group of high EPL countries.¹⁹ Estimating a pooled VAR for both groups shows that uncertainty

¹⁹As a robustness test, we re-run the analysis excluding both Japan and Switzerland. Neglecting the two countries does not significantly change the results (see Figure 12 in Appendix D).

Country	Average EPL (1985-2013)
United States	0.26
Canada	0.92
United Kingdom	1.17
Switzerland	1.60
Median	1.62
Japan	1.62
France	2.39
Germany	2.65
Sweden	2.70
Italy	2.76

Table 3: High EPL vs. low EPL countries

Notes: This table ranks countries according to the strictness of employment protection. In order to calculate the ranking, we use the annual time series data of the OECD Employment Protection Database to calculate the average value of the strictness of employment protection individual and collective dismissals (EPRC.V1) - over time (from 1985 to 2013).

has indeed less deteriorating effects in countries with high employment protection. Figure 8 shows that the effect of a one standard deviation uncertainty shock is not only more contractionary in countries with high protection compared to countries with low labor protection, the negative effects are also more persistent.

The results presented in Figure 8 are consistent with the theoretical predictions outlined above. In countries with stricter employment protection legislation, it is more costly for firms to reduce employment. Hence, employment drops less in the light of an uncertainty shock. Consequently, due to the complementarity of capital and labor, firms do not cut investment by as much, causing production to contract less. Finally, a higher degree of labor protection transmits into a higher job security of employees. An increase in uncertainty lets employees worry less about their future income in case of high employment protection than in case of low employment protection. Households thus increase precautionary saving less and decrease consumption by less which causes a less pronounced drop of aggregate demand. These findings complement the literature on the importance of the labor channel in explaining the transmission of uncertainty shocks. However, it highlights a different mechanism. In contrast to Guglielminetti (2016), who

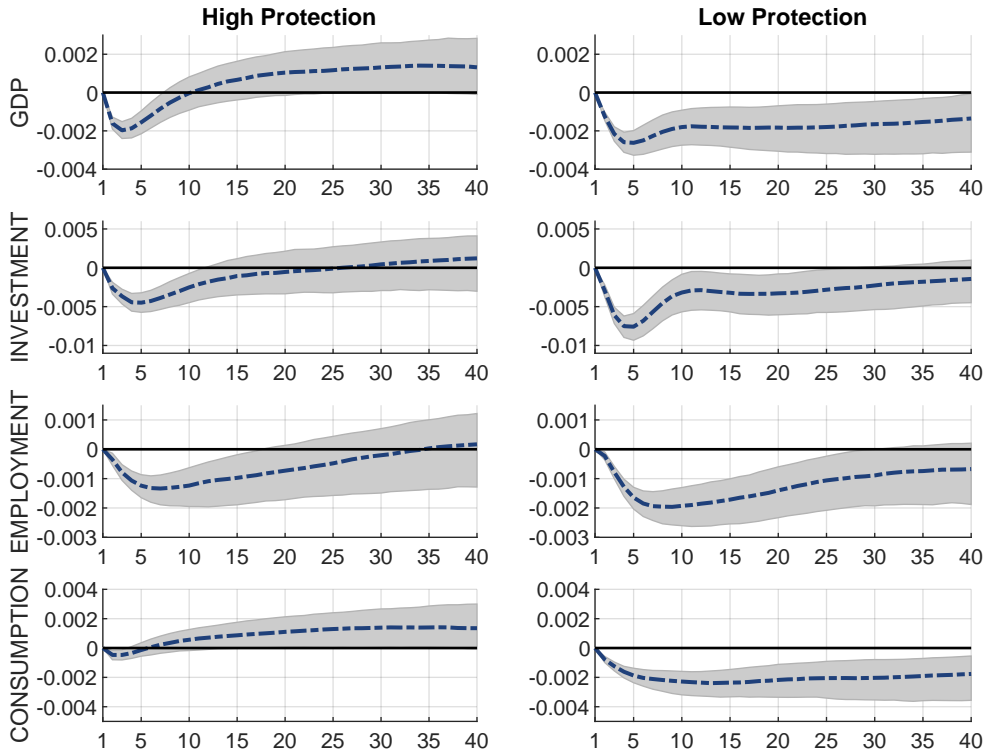


Figure 8: Impulse responses to an uncertainty shock for high EPL countries (left panel) and low EPL countries (right panel).

Notes: The dotted blue line depicts the posterior mean and the grey shaded area the 68% error bands for the impulse responses to an one standard deviation uncertainty shock. The estimation sample spans the period 1988Q1–2016Q3.

argues for the importance of hiring costs, our results indicate a prominent role of firing costs in explaining the dynamics of uncertainty shocks. From a theoretical point of view, the firing and hiring cost coexist next to each other, but are independent of each other. The combination of both channels determine the importance of the labor channel in the propagation of uncertainty shocks in the model. In a situation where firing costs are very high and hiring are zero, the labor channel would be almost irrelevant. On the other hand, in an economy with no firing costs and high hiring costs the labor channel is an important transmission mechanism.

7 Conclusion

In this paper we have introduced new internationally comparable measures of macroeconomic uncertainty for a large set of countries using data revisions in aggregate variable that are bound to the system of national accounts. We have set up an econometric model and constructed a new real-time data set of real GDP for 39 countries that serves as the basis for our estimations. Using real-time data permits us to obtain accurate estimates of uncertainty that an economic agent experienced at any given point in time, whereas existing measures of macroeconomic uncertainty base on forecast errors that are constructed with non real-time data.

In order to obtain real-time uncertainty estimates, we extended the data revision model proposed by Jacobs and van Norden (2011) such that it allows us to extract the volatility of the unpredictable part of future releases of the news component that forms our measure of macroeconomic uncertainty. We showed that the resulting uncertainty indicator for the United States has similar properties than the macroeconomic uncertainty measures proposed by Jurado et al. (2015). The revision based indicator is thereby less volatile than alternative measures such as the economic policy uncertainty index by Baker et al. (2016) or the VIX and the revision based indicator also identifies the same three major uncertainty shocks between 1965 and 2016. Namely, the recession in the 1970s, the early 1980s recession and the Great Recession of 2008. The revision based indicator reaches its highest peak during 1970s. Considering that the recession in the 1970s comprised the first oil price shocks, the collapse of the Bretton Woods System and the end of the post World War II economic expansion this seems coherent with a broader economic history perspective. Our empirical evaluation indicates a strong and negative relationship between the revision based uncertainty measures and the economy. Estimating VARs for the United States and the G7 countries shows that a one standard deviation shock in the revision based uncertainty indicators leads to a contraction in GDP, investment, employment and consumption.

The newly constructed uncertainty measures can be used to study uncertainty shocks in a cross-country setting. In this paper, we studied the importance of labor market frictions for the propagation of uncertainty shocks. In a VAR analysis, we found that uncertainty

shocks have more deteriorating effects in countries with a lower degree of EPL compared to countries with stricter EPL. Using the theoretical model of Bloom et al. (2018) with varying degree of firing costs, we could show that these empirical findings are in line with theory.

References

- S. R. Baker, N. Bloom, and S. J. Davis. Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636, 2016. 11, 12, 26
- S. Basu and B. Bundick. Uncertainty shocks in a model of effective demand. *Econometrica*, 85(3):937–958, 2017. 16
- U.-L. Bell. Adjustment costs, uncertainty and employment inertia. *Working Paper Series Bank of Spain*, (9620), 2016. 21
- T. Berger, S. Grabert, and B. Kempa. Global macroeconomic uncertainty. *Journal of Macroeconomics*, 53:42–56, 2017. 1, 3, 14, 15
- N. Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009. ISSN 1468-0262. doi: 10.3982/ECTA6248. URL <http://dx.doi.org/10.3982/ECTA6248>. 16
- N. Bloom. Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2):153–76, 2014. doi: 10.1257/jep.28.2.153. URL <http://www.aeaweb.org/articles.php?doi=10.1257/jep.28.2.153>. 1
- N. Bloom, M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry. Really uncertain business cycles. *Econometrica*, 86(3):1031–1065, 2018. 2, 20, 21, 22, 27
- J. Boysen-Hogrefe and S. Neuwirth. The impact of seasonal and price adjustments on the predictability of german gdp revisions. Technical report, Kiel Working Paper, 2012. 8, 9, 38
- M. Cacciatore and F. Ravenna. Uncertainty, wages, and the business cycle. In *29th Annual Meeting of the Canadian Macroeconomics Study Group, Montréal*, pages 6–7, 2015. 19
- A. Carriero, T. E. Clark, and M. Marcellino. Assessing international commonality in macroeconomic uncertainty and its effects. *Journal of Applied Econometrics*, 2019. 1, 3, 14, 15
- C. K. Carter and R. Kohn. On Gibbs sampling for state space models. *Biometrika*, 81(3):541–553, 09 1994. 7, 31

- E. Castelnuovo. Domestic and Global Uncertainty: A Survey and Some New Results. *CESifo Working Paper Series*, (7900), 2019. 13
- D. Croushore and T. Stark. A real-time data set for macroeconomists. *Journal of Econometrics*, 105(1):111 – 130, 2001. ISSN 0304-4076. doi: [https://doi.org/10.1016/S0304-4076\(01\)00072-0](https://doi.org/10.1016/S0304-4076(01)00072-0). URL <http://www.sciencedirect.com/science/article/pii/S0304407601000720>. Forecasting and empirical methods in finance and macroeconomics. 1
- P. de Jong. Rational economic data revisions. *Journal of Business Economic Statistics*, 5(4):539–548, 1987. 4
- A. Z. Fernandez, H. Branch, E. F. Koenig, and A. Nikolsko-Rzhevskyy. A real-time historical database for the oecd. *Globalization and Monetary Policy Institute Working Paper*, 96, 2011. 8, 17, 36
- S. Frühwirth-Schnatter. Data Augmentation and Dynamic Linear Models. *Journal of Time Series Analysis*, 15(2), 1994. 31
- R. Golinelli and G. Parigi. Real-time squared: A real-time data set for real-time gdp forecasting. *International Journal of Forecasting*, 24(3):368–385, 2008. 8, 9
- C. Grund. Severance payments for dismissed employees in germany. *European Journal of Law and Economics*, 22(1):49–71, 2006. 22
- E. Guglielminetti. The labor market channel of macroeconomic uncertainty. *Bank of Italy Temi di Discussione (Working Paper) No*, 1068, 2016. 19, 24
- J. Jacobs and S. van Norden. Modeling data revisions: Measurement error and dynamics of "true" values. *Journal of Econometrics*, 161(2):101–109, 2011. URL <https://EconPapers.repec.org/RePEc:eee:econom:v:161:y:2011:i:2:p:101-109>. 1, 4, 5, 26
- K. Jurado, S. C. Ludvigson, and S. Ng. Measuring uncertainty. *American Economic Review*, 105(3):1177–1216, 2015. doi: 10.1257/aer.20131193. URL <http://www.aeaweb.org/articles.php?doi=10.1257/aer.20131193>. 1, 2, 3, 5, 11, 12, 17, 18, 26

- G. Kastner and S. Frühwirth-Schnatter. Ancillarity-sufficiency interweaving strategy (asis) for boosting mcmc estimation of stochastic volatility models. *Computational Statistics & Data Analysis*, 76:408–423, 2014. 7, 32, 33
- S. Kim, N. Shephard, and S. Chib. Stochastic volatility: Likelihood inference and comparison with arch models. *The Review of Economic Studies*, 65(3):361–393, 1998. ISSN 00346527, 1467937X. URL <http://www.jstor.org/stable/2566931>. 6
- K. Kishor and E. F. Koenig. Var estimation and forecasting when data are subject to revision. *Journal of Business Economic Statistics*, 30(2):181–190, 2012. 4
- F. Kramarz and M.-L. Michaud. The shape of hiring and separation costs in france. *Labour Economics*, 17(1):27–37, 2010. 22
- S. Leduc and Z. Liu. Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82:20–35, 2016. 19
- K. Lee, N. Olekalns, K. Shields, and Z. Wang. Australian real-time database: An overview and an illustration of its use in business cycle analysis. *Economic Record*, 88(283):495–516, 2012. 8, 36
- N. Mankiw and M. Shapiro. News or noise: An analysis of gnp revisions. *Survey of Current Business*, 66:20–25, 1986. 4
- N. Mankiw, D. E. Runkle, and M. D. Shapiro. Are preliminary announcements of the money stock rational forecasts? *Journal of Monetary Economics*, 14(1):15 – 27, 1984. ISSN 0304-3932. doi: [https://doi.org/10.1016/0304-3932\(84\)90024-2](https://doi.org/10.1016/0304-3932(84)90024-2). URL <http://www.sciencedirect.com/science/article/pii/0304393284900242>. 4
- W. McCausland, S. Miller, and D. Pelletier. Simulation smoothing for state-space models: A computational efficiency analysis. *Computational Statistics Data Analysis*, 55(1): 199–212, 2011. URL <https://EconPapers.repec.org/RePEc:eee:csdana:v:55:y:2011:i:1:p:199-212>. 7, 34
- H. Mumtaz and K. Theodoridis. Common and country specific economic uncertainty. *Journal of International Economics*, 105:205–216, 2017. 1, 3, 13, 15
- OECD. OECD Main Economic Indicators (MEI). Original Release Data and Revisions Database, 2017. <http://stats.oecd.org/mei/default.asp?rev=1>. 8, 36

- C. Redl. The impact of uncertainty shocks in the united kingdom. *Staff Working Paper*, (695), 2017. 13
- C. Redl. Uncertainty matters: evidence from close elections. 2018. 1, 3, 15
- T. J. Sargent. Two models of measurements and the investment accelerator. *Journal of Political Economy*, 97(2):251–287, 1989. ISSN 00223808, 1537534X. URL <http://www.jstor.org/stable/1831313>. 4
- H. Scarf. The optimality of (5, 5) policies in the dynamic inventory problem. 1959. 21
- C. Sleeman. Analysis of revisions to quarterly gdp—a real-time database. *Reserve Bank of New Zealand Bulletin*, 69(1):31–44, 2006. 8
- Y. Yu and X.-L. Meng. To center or not to center: That is not the question an ancillarity–sufficiency interweaving strategy (asis) for boosting mcmc efficiency. *Journal of Computational and Graphical Statistics*, 20(3):531–570, 2011. 32

Appendix A Posterior Simulations

In this section we describe the blocks of our Gibbs sampling procedure outlined in section 2. Note that Equations (2) and (6) can be rewritten as

$$Y_t = Z\alpha_t, \quad (11)$$

$$\alpha_t = \varphi_t + T_t\alpha_{t-1} + RD_t^{1/2}\eta_t, \quad (12)$$

with

$$R = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, D_t = \begin{bmatrix} \exp(h_t^{\tilde{y}}) & 0 & 0 & 0 \\ 0 & \exp(h_t^{\nu}) & 0 & 0 \\ 0 & 0 & \exp(h_t^{\zeta^1}) & 0 \\ 0 & 0 & 0 & \exp(h_t^{\zeta^L}) \end{bmatrix}.$$

A.1 Drawing News, Noise and True Values

Conditional on the stochastic volatilities and the VAR coefficients of the state space model (c_t and ρ_t), we draw α_t for $t = 1, \dots, T$, using the forward filtering backward sampling procedure of Carter and Kohn (1994) and Frühwirth-Schnatter (1994), where (11) serves as observation equation and (12) as state equation.

A.2 Drawing Stochastic Volatility

Conditional on news, noise, true values and the VAR coefficients of (12), we obtain draws for the stochastic volatilities (h_t^x) using the estimation method proposed in Kastner and Frühwirth-Schnatter (2014). We thus estimate the stochastic volatilities by interweaving estimation models specified in a centered (C) and a non-centered (NC) parameterization using the ancillarity-sufficiency interweaving strategy (ASIS) detailed by Yu and Meng (2011). This estimation strategy addresses the trade-off in terms of sampling efficiency depending on the value of the persistence parameter ϕ . Kastner and Frühwirth-Schnatter (2014) show that this estimation strategy outperforms estimators using pure centered or non-centered parameterizations.

Starting from Equation (4), we assume that:

$$\sigma_t^i \eta_t^i = e^{h_t^i/2} \eta_t^i \quad (13)$$

$$h_t^i = \mu^i + \phi^i (h_{t-1}^i - \mu^i) + \tau^i \epsilon_t^i, \quad (14)$$

with $\epsilon_t^i \sim N(0, 1)$ and $x = \tilde{y}, \nu, \zeta 1, \zeta L$. One can express the centered parametrization of Equation (16) as a non-centered parametrization. In the non-centered parametrization the volatility components are assumed to follow the following process:

$$\tilde{h}_t^i = \phi^i \tilde{h}_{t-1}^i + \epsilon_t^i, \quad (15)$$

with $\epsilon_t^i \sim N(0, 1)$ and $x = \tilde{y}, \nu, \zeta 1, \zeta L$.

We can rewrite Equation (13) as

$$\tilde{\sigma}_t^i = h_t^i + \log((\eta_t^i)^2) \quad (16)$$

with $\eta_t^i \sim N(0, 1)$ and $\tilde{\sigma}_t^i$ denotes $\log((\sigma_t^i \eta_t^i)^2)$. The fact that we can approximate the distribution of $\log((\eta_t^i)^2)$ by a mixture of normal distributions, that is, $\log((\eta_t^i)^2) | r_t^i \sim N(m_{r_t^i}^i, (s_{r_t^i}^i)^2)$ with r_t indicating the mixture component, we can rewrite Equation (16) as a linear and conditionally Gaussian state space model,

$$\tilde{\sigma}_t^i = m_{r_t^i}^i + h_t^i + \eta_t^i, \quad (17)$$

with $\eta_t^i \sim N(0, s_{r_t}^{2i})$. Based on Equation (17), we apply a MCMC procedure outlined in Kastner and Frühwirth-Schnatter (2014) that interweaves the centered and non-centered specification.

We rely on the priors proposed in Kastner and Frühwirth-Schnatter (2014). That is, μ follows a normal distribution with mean b_μ and variance B_μ , i.e. $\mu \sim N(b_\mu, B_\mu)$. The persistence parameter ϕ follows a Beta distribution, i.e. $B(a_0, b_0)$. Finally, for the volatility parameter σ , they chose $\sigma^2 \sim B_\sigma \chi_1^2 = G(1/2, 1/2B_\sigma)$. We use the same priors for the centered and non-centered parameterization. We calibrate the parameters as follows: $b_\mu = 0$, $B_\mu = 100$, $a_0 = 5$, $b_0 = 1.5$ and $B_\sigma = 1$.

The MCMC interweaving procedure consists of the following steps:

1. We sample the volatilities using the all without a loop (AWOL) procedure by drawing from $h_{[-0]}^i | \tilde{\sigma}^i, r^i, \mu^i, \phi^i, (\eta^i)^2$. The initial values is drawn from $h_0^i | h_1^i, r^i, \mu^i, \phi^i, (\eta^i)^2$.
2. We sample μ^i, ϕ^i , and $(\eta^i)^2$ using Bayesian regression. We use a 2-block samples, where we draw $(\eta^i)^2$ from $(\eta^i)^2 | h^i, \mu^i, \phi^i$ and we jointly sample μ^i and ϕ^i from $\mu^i, \phi^i | h^i, (\eta^i)^2$. Because the chosen priors are not analytically tractable, we calculate updates via a Metropolis-Hastings (MH) algorithm.
3. Move to NC by the deterministic transformation $\tilde{h}_t^i = \frac{h_t^i - \mu^i}{\eta^i}$
4. Redraw $\mu^i, \phi^i, (\eta^i)^2$ for NC specification. We need MH only to update ϕ^i by drawing from $\phi^i | \tilde{h}^i$. We can Gibbs-update μ^i and $(\eta^i)^2$ jointly from $\mu^i, (\eta^i)^2 | \tilde{\sigma}^i, \tilde{h}^i, r^i$.
5. Move back to C by calculating $h_t^i = \mu^i + \eta^i \tilde{h}_t^i$ for all t
6. Draw the indicators r^i (C). We update the mixture component indicators r^i from $r^i | \tilde{\sigma}^i$ using inverse transform sampling.

A.3 Drawing Time-Varying Coefficients

Conditional on news, noise, true values and the stochastic volatilities, we draw the time-varying coefficients of Equation (12), by considering the process of true GDP \tilde{y}_t to be represented by the following state space model

$$\tilde{y}_t = Z_t \alpha_t + G_t u_t, \quad (18)$$

$$\alpha_t = T \alpha_{t-1} + H_{i,j} e_t \quad (19)$$

with

$$Z_t = \begin{bmatrix} 1 & \tilde{y}_t \end{bmatrix}, \alpha_t = \begin{bmatrix} c_t \\ \rho_t \end{bmatrix}, G_t = \begin{bmatrix} \exp(h_t^{\tilde{y}}) & \exp(h_t^{\nu}) \end{bmatrix}, \quad (20)$$

$$u_t = \begin{bmatrix} u_t^{\tilde{y}} \\ u_t^{\nu} \end{bmatrix}, T = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, H_{i,j} = \begin{bmatrix} \sigma_{i,j}^{c_{i,j}} & \sigma_{i,j}^{\rho_{i,j}} \end{bmatrix}, e_t = \begin{bmatrix} e_t^{c_t} \\ e_t^{\rho_t} \end{bmatrix}.$$

We obtain estimates for c_t and ρ_t using the method proposed by McCausland et al. (2011).

We set up the diagonal matrix Ω as follows:

Diagonal Matrix Ω

$$\Omega = \begin{bmatrix} \Omega_{11} & \Omega_{t/t-1} & 0 & \cdots & 0 \\ \Omega_{t/t-1} & \Omega_{tt} & \Omega_{t/t-1} & \ddots & \vdots \\ 0 & \Omega_{t/t-1} & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & \Omega_{tt} & \Omega_{t/t-1} \\ 0 & \cdots & 0 & \Omega_{t/t-1} & \Omega_{nn} \end{bmatrix} \quad (21)$$

Diagonal Elements

$$\Omega_{11} = Z_1' A_{11,1} Z_1 + A_{22,1} + P_1^{-1} \quad (22)$$

$$\Omega_{tt} = Z_t' A_{11,t} Z_t + 2A_{22,t} \quad (23)$$

$$\Omega_{nn} = Z_n' A_{11,n} Z_n + A_{22,n} \quad (24)$$

$$(25)$$

Off-Diagonal Elements

$$\Omega_{t/t-1} = -A_{22,t} \quad (26)$$

$$(27)$$

with

$$A_t = \begin{bmatrix} (G_t' G_t)^{-1} & 0 \\ 0 & (H_{i,j}' H_{i,j})^{-1} \end{bmatrix} \quad (28)$$

$$(29)$$

We set up the co-vector C the following way:

Covector

$$C_1 = \begin{bmatrix} C_1 \\ C_{tt} \\ \vdots \\ C_{nm} \end{bmatrix}. \quad (30)$$

with

$$C_1 = Z_0' A_{11,0} \tilde{y}_0 + P_1^{-1} a_1 \quad (31)$$

$$C_{tt} = Z_t' A_{11,t} \tilde{y}_t \quad (32)$$

$$C_{nm} = Z_T' A_{11,T} \tilde{y}_T \quad (33)$$

We solve this system by first computing the Cholesky decomposition $\Omega = LL'$ that We implement directly in Julia. Because of the band structure of Ω , the decomposition is incredibly fast. In a second step, we draw $e_t \sim N(0, 1)$ and solve $La = c$ for a . Finally, we use back-substitution in order to solve $L'h = a + e$ for h .

Appendix B Real-Time Data

We use data revisions in macroeconomic aggregates to obtain measures of macroeconomic uncertainty for various OECD countries. Real-time data releases of macroeconomic aggregates are thereby the key ingredient to construct the uncertainty indicator. In our preferred specification, we base the indicator on nominal GDP. In order to obtain a comprehensive data set for various countries, we need to tap and combine several data sources. Appendix B describes these various data sources and outlines the construction of our data base in great detail.

B.1 Real-Time Data: Main Source

The largest part of our data is provided by *Original Release Data and Revisions Database*. The *Original Release Data and Revisions Database* is part of OECD Main Economic Indicators database (OECD, 2017) and represents the central data source of this project. The database provides different releases of macroeconomic aggregates for many countries. This study uses data from 32 countries including Australia, Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Great Britain, Greece, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Russia, South Africa, Spain, Sweden, Switzerland, Turkey, USA. Unfortunately, *Original Release Data and Revisions Database* provides releases of macroeconomic variables only since 1999. For data prior to 1999, we need to rely on other data provider. We primarily use the data made available by the Federal Reserve of Dallas for releases prior to 1999. Fernandez et al. (2011) collect real-time data for various economies including those that we use in this study. The authors assemble the dataset from original quarterly releases of different macroeconomic aggregates from 1962 to 1998. We currently use their data for all countries except the Australia, New Zealand, and U.S.. For the U.S., we use data provided by the Federal Reserve of Philadelphia as they provide more exhaustive data compared to the data provided by Federal Reserve of Dallas. We use Australian nominal GDP data provided by the Australian Real-Time Macroeconomic Database (Lee et al. (2012)). For New Zealand, we use the "Real-Time GDP Data" data set from the Reserve Bank of New Zealand that provides nominal GDP releases. Table 1 provides an overview of the countries included in our study, the data provider and the first available data point.

Figure 9 shows the average of the 10th revision of year-over-year growth rates of nominal GDP. Thereby, most countries have a statistical significant downward bias. That is, ten quarter after the first release, most countries countries publish on average a higher growth rate.

B.2 Real-Time Data: Practical decisions

Australia

We use real-time data from the Real-Time Macroeconomic Database provided by the

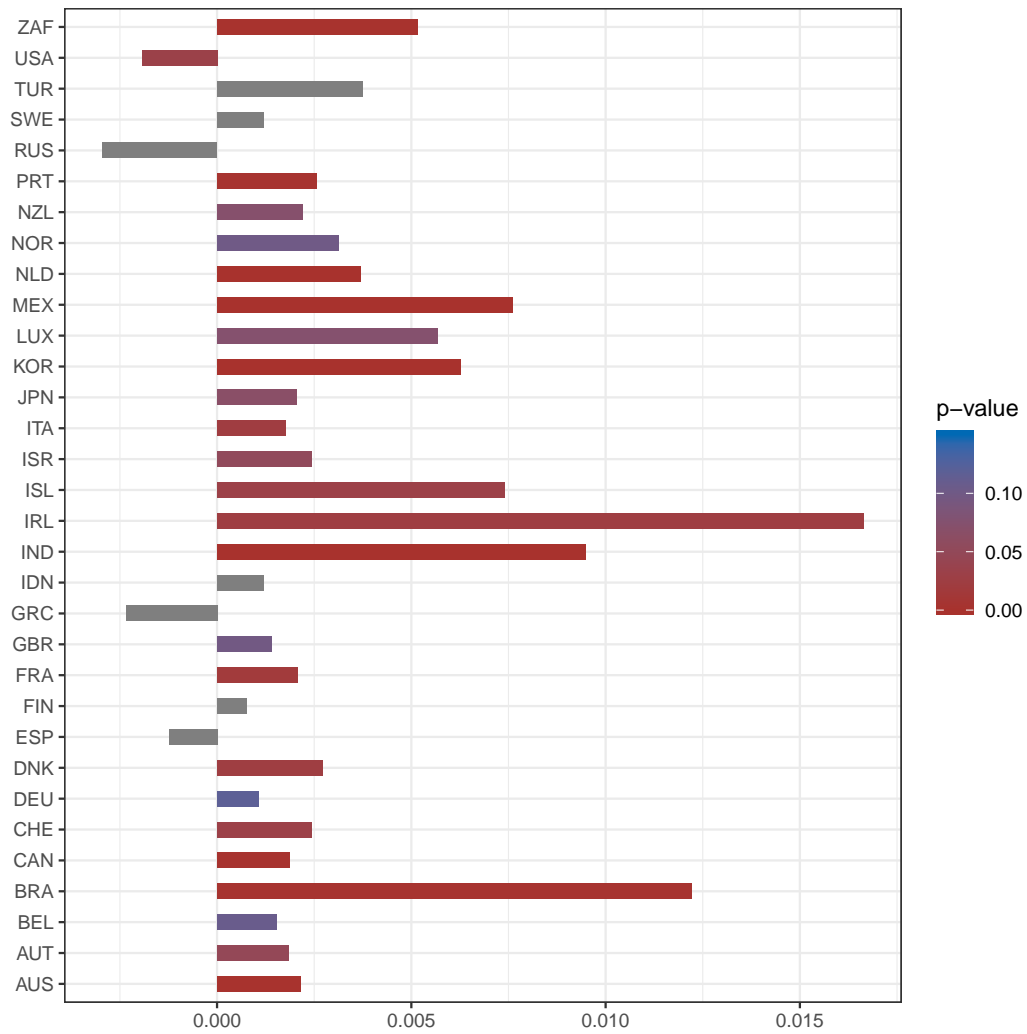


Figure 9: Nominal GDP Growth (yoy): Mean of the 10th revisions for the period from 2000 Q1 to 2016Q3.

University Melbourne Macroeconomics Research Unit. The 1973Q3 vintage contains unusual entries. The 1973Q2 vintage contains combined figures for the 1972Q3-Q4 and 1973Q1-Q2 reference dates. We split the combines figures by using the share of the 1973Q4 vintage.

Canada

We use real-time data provided by the Federal Reserve of Dallas for releases prior to 1982. For the time span between 1982 and 1999, we rely on real-time data provided by the Bank of Canada. Finally, from 1999 onward, we use real-time data provided by the OECD Main Economic Indicators database. The data provided by the OECD Main Economic Indicators database and the Bank of England are virtually identical after 1999, except for the quarters 2000Q2 to 2001Q1. For this quarter, we opt for data provided by the Bank of Canada as they appear to be by far less volatile.

Germany

We use real-time data provided by the Federal Reserve of Dallas for releases prior to 1999. The dataset provides GNP until February 1993. Thereafter the dataset provided by the Federal Reserve of Dallas contains data on GDP. Furthermore, the dataset contains vintages for West Germany until November 1993. From February 1994 on-wards, the dataset provides vintages for the unified Germany. Unfortunately, the length of the vintages between February 1994 and August 1995 is critically short. Hence, we use vintages of GNP for West Germany until May 1995 (provided by Boysen-Hogrefe and Neuwirth (2012)). From August 1995 onwards, we use GDP for united Germany provided by the Federal Reserve of Dallas. Finally, starting from 1999, we use data on GDP provided by the OECD Main Economic Indicators database.

B.3 VAR Data

Quarterly GDP Japan

We obtain quarterly real GDP for Japan from 1994Q1 until now from the OECD database. The Economic and Social Research Institute of Japan provides Real GDP Growth prior to 1994 at 2000 prices that is used to calculate Real GDP until 1980. Real GDP Growth prior to Q1 1981 is calculated from the last growth rate of each window for a certain quarter from our release dataset.

Appendix C Uncertainty Estimates

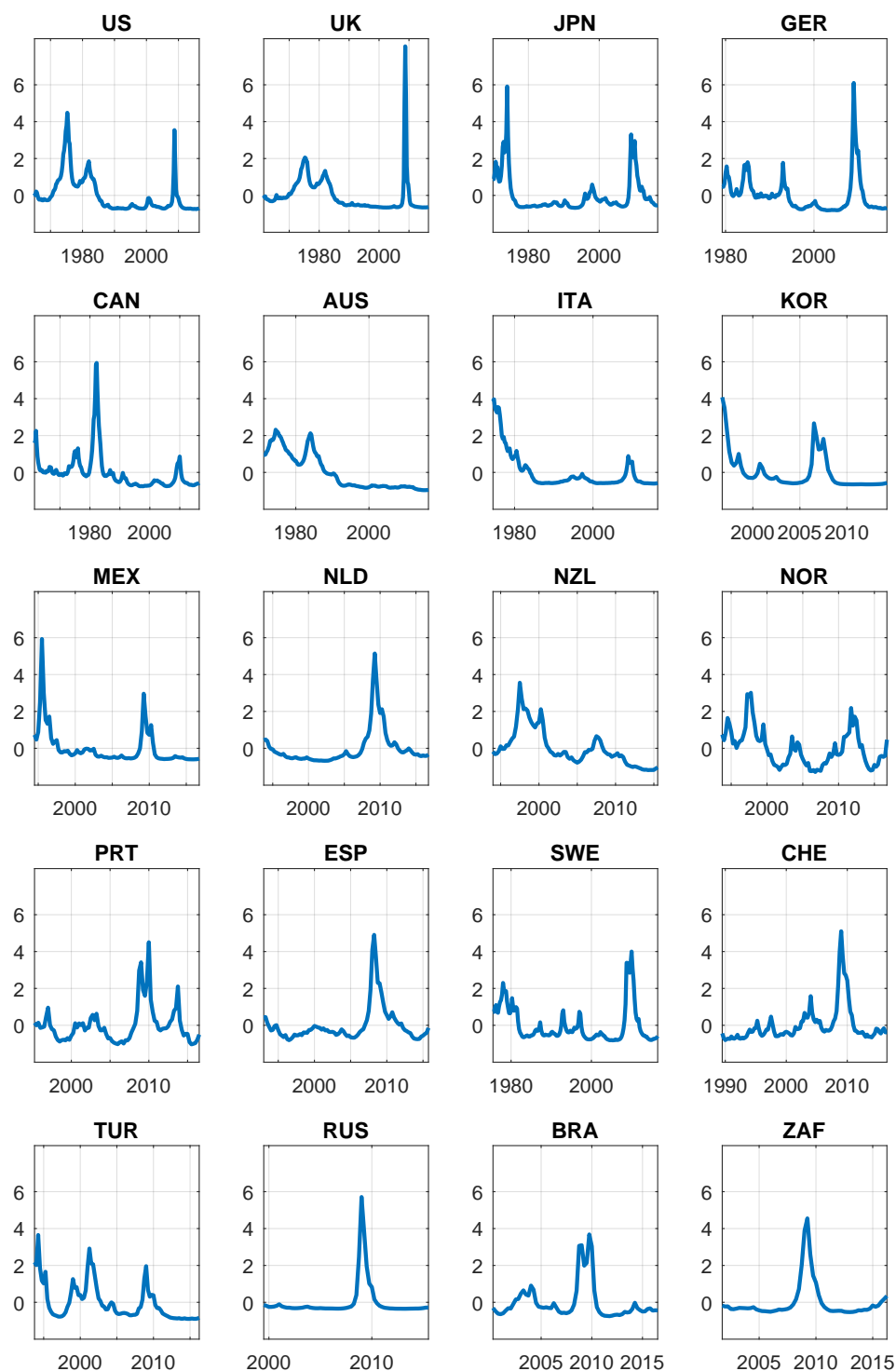


Figure 10: Macroeconomic Uncertainty

Notes: This figure presents uncertainty indicators based on GDP revisions. All indicators are demand and standardized to unit variance.

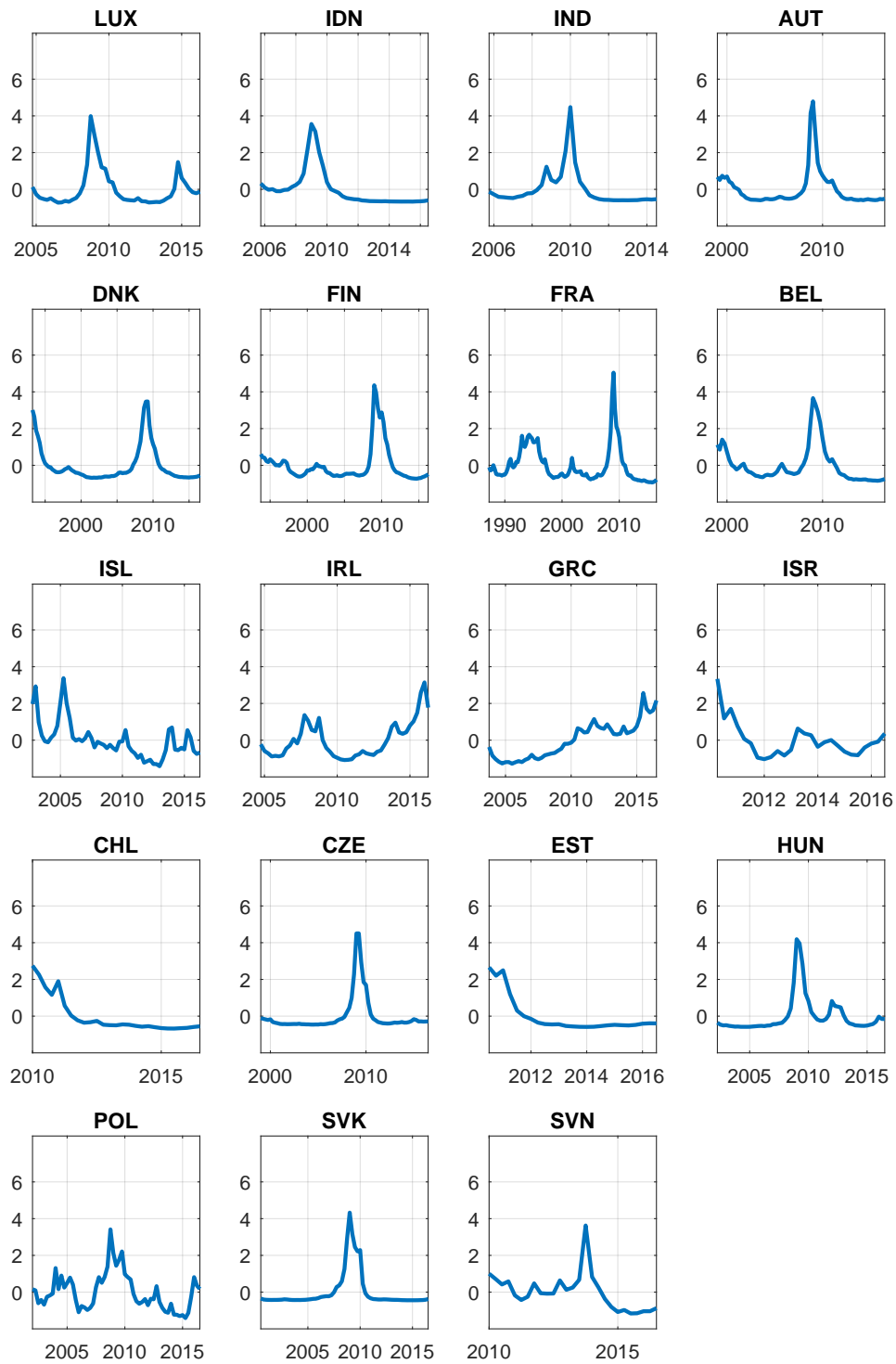


Figure 11: Macroeconomic Uncertainty (cont.)

Notes: This figure presents uncertainty indicators based on GDP revisions. All indicator are demand and standardized to unit variance.

Appendix D Robustness

D.1 Selected High and Low EPL Countries

In order to empirically evaluate the effect of employment protection legislation (EPL) on the propagation of uncertainty shocks, we estimate a VAR for countries with stricter EPL and a VAR for countries with a lower degree of EPL. As mentioned in the main text, we use the OECD Employment Protection Database to split countries into two groups. The groups selected in Table 3 mirror our expectations with Anglo-Saxon economies displaying a low degree and continental European countries showing higher degree of employment protection standards. The OECD Employment Protection Database attests Switzerland and Japan have a very similar degree of employment protection legislation. In our baseline specification, we include Switzerland in the group with low labor protection and Japan in the group of high EPL countries. As a robustness test, we re-run the analysis excluding both Japan and Switzerland. Figure 12 shows that neglecting the two countries does not significantly change the results. Estimating a pooled VAR for both groups shows that uncertainty has still less deteriorating effects in countries with high employment protection.

D.2 Incorporating Estimation Uncertainty

We now investigate the impact of the estimation uncertainty surrounding our measures of macroeconomic uncertainty on our main findings. Instead of using the mean of the posterior distribution of our uncertainty measure, we now simulate the posterior distribution of the VAR model conditional on the draws from the posterior distribution of our uncertainty indicator. Figure 13 compares the impulse responses functions of high protection countries to low protection countries. Although the overall effects are somewhat weaker than the ones shown in Figure 8, the relative precision does not change in a significant manner. Most importantly, our principal findings do not change when taking into account the uncertainty surrounding our uncertainty estimates. Figure 14 presents the overall effects for the G7 average. The responses of the variables seem also somewhat weaker than the ones reported in Figure 6. The impulse response functions of consumption are additionally not clearly negative anymore. The impulse responses

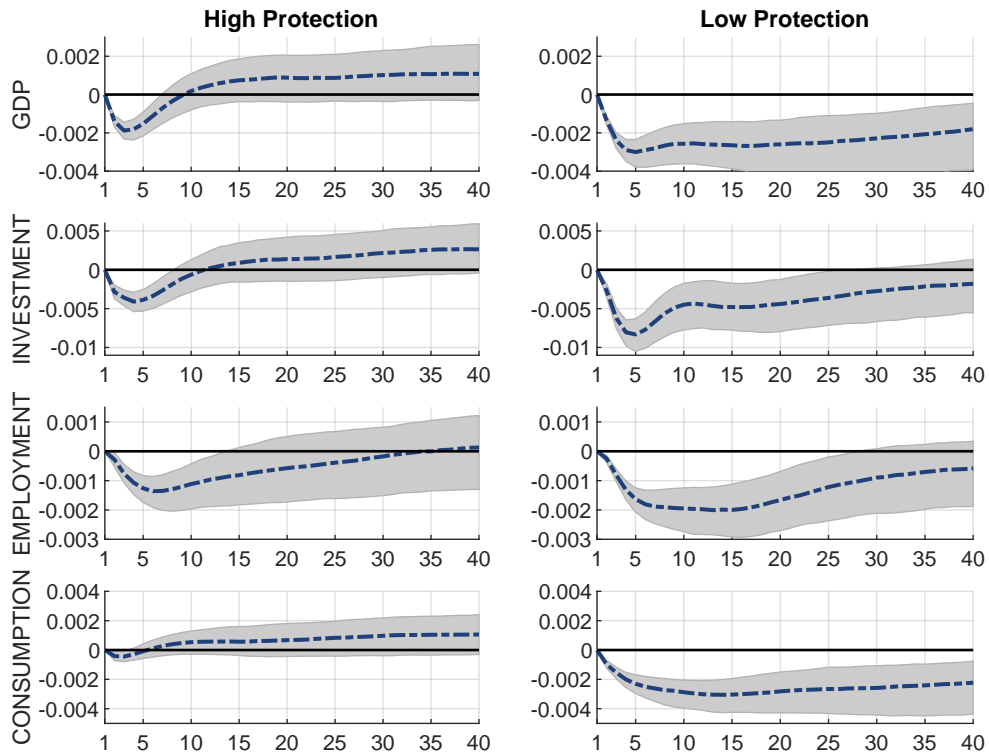


Figure 12: Impulse responses to an uncertainty shock for high EPL countries (left panel) and low EPL countries (right panel) without Japan and Switzerland.

Notes: The dotted blue line depicts the posterior mean and the grey shaded area the 68% error bands for the impulse responses to an one standard deviation uncertainty shock. The estimation sample spans the period 1988Q1–2016Q3.

for all other variable however appear robust with regards to the inclusion of the added estimation uncertainty.

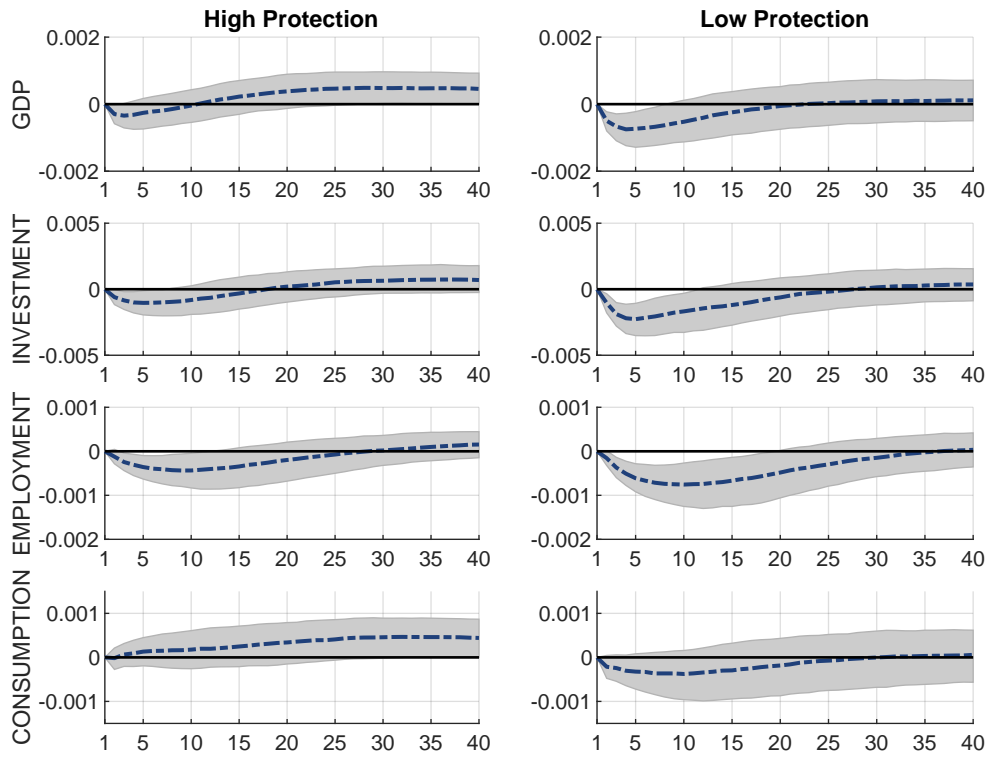


Figure 13: Impulse responses to an uncertainty shock for high EPL countries (left panel) and low EPL countries (right panel), including the uncertainty surrounding data revisions based uncertainty indicator.

Notes: The dotted blue line depicts the posterior mean and the grey shaded area the 68% error bands for the impulse responses to an one standard deviation uncertainty shock. The estimation sample spans the period 1988Q1–2016Q3.

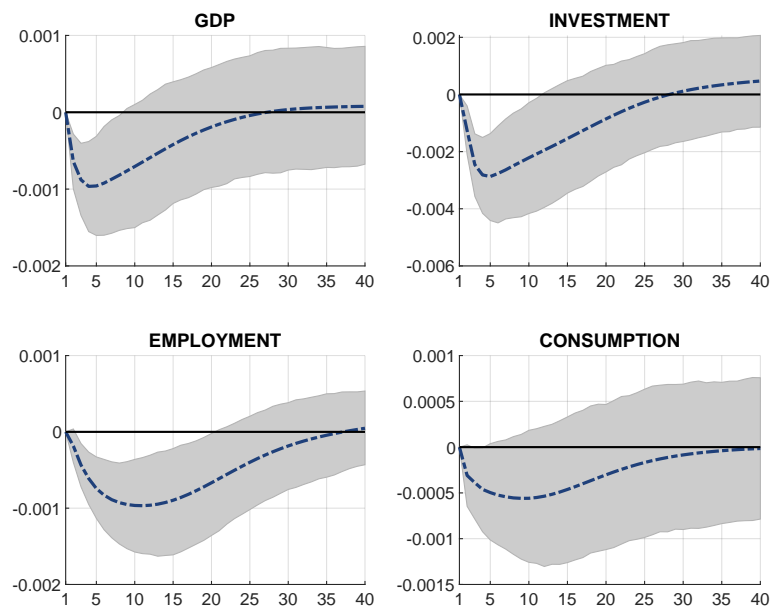


Figure 14: Impulse responses to an uncertainty shock for the group of G7 countries, including the uncertainty surrounding data revisions based uncertainty indicator.

Notes: The dotted blue line depicts the posterior mean and the grey shaded area the 68% error bands for the impulse responses to an one standard deviation uncertainty shock. The estimation sample spans the period 1988Q1–2016Q3.