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DEP (Socioeconomics) Discussion Papers
Macroeconomics and Finance Series
6/2014

2nd updated version

Hamburg, 2014

Real-time Macroeconomic Data and Uncertainty

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July 14, 2015

Abstract

Most macroeconomic data is continuously revised as additional information becomes available. We suggest that revisions of data is an increasingly important source of uncertainty about the state of the economy and offer an alternative channel of uncertainty - data uncertainty. This paper adds on the uncertainty literature and focuses on data uncertainty, which originates in the revision structure of data. We find that apart from the general and economic policy uncertainty, the data uncertainty has been rising throughout the past decade in the US and Euro area. To the best of our knowledge, this is the first study of Euro area data uncertainty. Our analysis shows that there is a positive lagged effect of economic policy uncertainty on data uncertainty for both regions. Our finding corresponds to the recent literature on increased macroeconomic and economic policy uncertainty during and after the "Great Recession".

Keywords: forecasting, information content, uncertainty, revisions, revision errors, entropy, signal-to-noise ratio, integrated signal-to-noise ratio, recession, EPU, VSTOXX, VIX

JEL classification: C53, C8, D80, E3

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[‡]The authors thank organizers and participants of the "Uncertainty and Economic Forecasting" Workshop (London, UK), the "Fifth Conference on Recent Developments in Macroeconomics" (ZEW, Mannheim, Germany), the "34th International Symposium on Forecasting" (Rotterdam, Netherlands) and DStatG2014 for useful comments and suggestions.

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1 Introduction

The recent discussion in the literature highlights that business cycle facts might have changed (Ng and Wright, 2013) during and in the aftermath of the "Great Recession", not only regarding real variables but regarding uncertainty as well (Bloom, 2014; Baker et al., 2014). This paper adds on the uncertainty literature (Bloom, 2009) and focuses on data uncertainty, which originates in the revision structure of data. We find that apart from the general and economic policy uncertainty, the data uncertainty has been rising throughout the past decade in the US and Euro area. Our analysis shows that there is a positive lagged effect of economic policy uncertainty on data uncertainty for both regions.

Researchers have been applying several empirical proxy variables for the latent (unobservable) variable "economic uncertainty". Those measures of general macroeconomic uncertainty are: stock market volatility, cross-sectional dispersion in forecaster beliefs, aggregated individual confidence bounds from surveys of professional forecasters, other survey measures as for example Bachmann et al. (2013)[1] or the "surprise" index suggested by Scotti (2013). A very recent paper by Jurado et al. (2015) applies statistical decompositions to identify common macroeconomic aspects of uncertainty based on factor models. Other measures are based on content analysis of news from the media as by Alexopoulos and Cohen (2009), Baker and Bloom (2013), Baker et al. (2013) or Donadelli (2014). Especially the uncertainty index by Baker et al. - economic policy uncertainty index (EPU) - is widely used in the literature and can be considered a special case of general macroeconomic uncertainty, viz. economic policy uncertainty.

Apart from the general economic and economic policy uncertainty there is uncertainty that originates in data. Data uncertainty is an important aspect when it comes to the predictability of macroeconomic time series. The main driving force of uncertainty here stems from short-horizon revisions of data: Revisions are usually caused by replacing preliminary data with later data, replacing judgmental projections with source data, changing definitions and estimation procedures or by updating the base year in real estimates (Young, 1994, p.63). McNees (1989) argues that there is a certain trade-off between timelines of data and its reliability. Patterson and Heravi (1991, p.49) showed that there are gains associated with the annual revision process throughout the range of vintages[2] and the results of estimations using particular vintage

[1] Bachmann et al. (2013) computed a survey-based uncertainty measures for the US and Germany.The German data index is constructed from the monthly IFO Business Climate Survey and the US index is based on the Federal Reserve Bank of Philadelphia's Business Outlook Survey. Refer to the details to Bachmann et al. (2013).

[2] Following the definition by Croushore and Stark (2003, p.605): a vintage captures "...data set corresponding to

have to be assessed for their sensitivity with respect to different revisions. Especially in the short-run, revisions may significantly affect the outcome of a model (Croushore, 2011, p.77).

The usage of a certain vintage can play an important role in policy decision making and forecasting, since policymakers depend on accurate assessments of the state of the economy.[3] A large string of the "real-time" literature focuses on predictability of revisions and applies tests inspired by Mincer and Zarnowitz (1969) or Nordhaus (1987).[4]
Furthermore information content or informativeness of data depends not only on the fact, that revision shocks are white noise but merely on the scope of revision and therefore on the degree of uncertainty at the time of estimate release.

Macroeconomic data uncertainty during the "Great Recession" and afterwards, however, has not been analyzed so far. In our paper we add to the literature on increased uncertainty and evaluate the data quality of different vintages of major real macroeconomic variables, such as real gross domestic product (GDP), private consumption, government consumption, investment, exports and imports as published by Eurostat. Moreover we investigate data uncertainty in the US real GDP data released by the Federal Reserve Bank of Philadelphia (FED). The real time revision dynamics is analysed for 159 vintages, estimates covering the period first quarter of 1991 until the third quarter of 2013, released between January 2001 and March 2014.

Previous studies deal with US-macroeconomic data, mainly the Survey of Professional Forecasters (SPF) and calculated uncertainty based on probability density of forecasts.[5] For revision analysis only few studies are based on real time data[6], to the best of our knowledge only Giannone et al. (2012)[7] so far for the Euro area macroeconomic data[8].

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the information set at a particular date...".

[3]See Swanson and Dijk (2006, p.24), Croushore and Stark (2003, 612-614), Croushore (2006, p.974).

[4]See for instance Ott (1989) using German data and Mankiw and Shapiro (1986); Oeller and Barot (2000); Oeller and Hansson (2004); Swanson and Dijk (2006); Clements et al. (2007); Patton and Timmermann (2012); Clements (2012a); Messina et al. (2014) using US data. An excellent overview of revision analysis literature since the 1960s can be found in Croushore (2006).

[5]US SPF forecasts were examined by Rich and Tracy (2010); Patton and Timmermann (2012); Clements (2012b) and Rich et al. (2012) used the European Central Bank SPF forecasts to estimate uncertainty.

[6]For example, German real time data was analyzed by Kholodilin and Siliverstovs (2009), US revisions were subject of studies i.e. by Croushore (2010); Patton and Timmermann (2012); Clements (2012a); Aruoba (2008); Aruoba and Diebold (2010).

[7]Giannone et al. (2012) describe primarity the Euro area dataset, the same that we use within this paper and discuss its characteristics based on descriptive statistics.

[8]Rich et al. (2012) calculated uncertainty based on ECB SPF forecasts, though neither revisions nor real time analysis have been subjects of their interest. Marcellino and Musso (2011) study euro area output gap estimates in real-time context.

Hereby we offer an alternative channel of uncertainty which orginates in revisions of data. The main findings of our analysis are: data uncertainty measured by entropy and signal-to-noise ratios has been growing continuously over the past decade for the US and the Euro area, though the magnitude of this effect differs across variables. Moreover, economic policy uncertainty shocks in the Euro area are Granger-causal to an increase in data uncertainty.

This paper is organized as follows: Section 2 describes the data set we have been working with as well as computations made for the analysis. We show in section 3 that our calculations for the most variables are based on true revision errors rather than forecast errors and are subject to news rather than noise. In section 4 we introduce the methods used for the analysis. Our findings are presented in section 5 for the US and the Euro area. Furthermore, in section 6 we analyze dynamic relationships between entropy measures and general uncertainty as well as economic policy uncertainty. The subsequent section 7 summarizes and discusses overall findings.

2 Data

Throughout this paper we measure the information content of Euro area revision errors for the major real macroeconomic variables published by Eurostat and the US real GDP series released by Federal Reserve Bank of Philadelphia. Detailed information about the variables and its sources is delivered in appendix A. The despription of the complete dataset is available by Giannone et al. (2012).

Eurostat revisions are available from January 3^{rd} 2001 until March 5^{th} 2014. For each quarter the flash release of variables is announced 45 days and revised flash 65 days after the end of the quarter. As more information becomes published, the final released is available 100 days after. The detailed release scheme is given in Table 1.[9] Additionally to the revision scheme described above, benchmark revisions take place about every five years, due to changes in the methodology, changes in the base year or – in the Euro area case – due to changes in regional coverage. To hold the results comparable we apply the same revision scheme to the US data as well.

[9] Eurostat release policy is presented in EUROSTAT (2013).

Table 1: Release scheme of Eurostat revisions

Quarter	flash(+45) release	revised flash (+65) release	final (+100) release
first	May	June	August
second	August	September	November
third	November	December	February
fouth	February	March	May

The number of vintages per year differs within the sample. At the beginning of the sample there have been ten revisions per year, while during the last seven years Eurostat revised monthly. Therefore we standardize vintages to twelve months per year. For this purpose we added vintages incorporating all information available at that point of time. This computation hold as a further advantage that it simplifies the comparison with the US data, as US sources revise monthly. Hence, the total number of vintages in the sample equals 159.

Another problem concerning Eurostat real time data is the beginning of our sample: There is a mismatch between the first vintage published on 3^{rd} January 2001 and the first data point (first quarter 1991). Hence, we assume that March 2001 estimates of 1991Q1-2000Q3 are final estimates and the revision errors for this vintage equal zero. The FED provides monthly revisions of quarterly estimates since August 1998. To avoid statistical problems, the data-set is trimmed here and the investigation starts April 2001.

For our analysis we compute annualized quarterly growth rates of macroeconomic variables $\hat{y}$ proxied by logged differences appropriately rescaled.[10]

$$\hat{y} = (\ln y_t - \ln y_{t-1}) * 400 \tag{1}$$

The revision error e_t^l at time t for the vintage l is defined as:

$$e_t^l = \hat{y}_t^L - \hat{y}_t^l \tag{2}$$

where $\hat{y}_t^l$ is the l^{th} revision for the period t.

The final release $\hat{y}_t^L$ in L for each quarter t is defined as officially claimed by Eurostat as “100 days after the end of the quarter”. Defined final release is held constant for all revision errors for t. Therefore the revision error of quarter t at vintage L equals zero. Further in 5.3 we imply more traditional in the literature definition of final release two years after the end of

[10] See Kirchgässner and Wolters (2007, p.7-8).

report quater.

To highlight recession periods, we use gray shaded areas in our graphs. The business cycle dating was taken from the Center of Economic Policy Research Business Cycle Dating Committee for the Euro area: peak in the first quarter 2008 and trough in the second quarter 2009, as well as the recent peak in the third quarter 2011.[11]

3 Sources of Revisions: News versus Noise

Before we start with the calculation of data uncertainty measures based on revisions, we have to be sure that our data is informative and does not contain noise.

Researchers since Mankiw and Shapiro (1986) assumed two characterizations of revisions: the agencies either add news or reduce noise by means of revisions. The revisions are considered optimal forecasts of final values if revision incorporates all available information and the final release only eliminates revision errors:

$$y_t^L = y_t^l + e_t^l \tag{3}$$

so that $y_t^l \perp e_t^l$ and $e_t^l \perp X_t^l, X_t^l \in \Omega^l$, where X_t^l indicates all known data at vintage l from information set Ω^l.

Alternatively, if the information is not included in the flash estimate then the revisions reduce noise. The difference between the flash release and the final release is captured by the measurement error u_t^l, which is independent of true value y_t^*, $y_t^* \perp u_t^l$.

$$y_t^l = y_t^* - u_t^l \tag{4}$$

The consequence of these characteristics shows up in the predictive ability of revisions. If the error is orthogonal to the revision than the revision cannot be predicted. Another case occurs when the final release is orthogonal to the error. In this case it is predictable and correlated with the flash release. Moreover, the variance and standard deviation should increase with each revision if it contains new information.(Croushore and Stark (2003, p.609-610),

[11] http://www.cepr.org/content/euro-area-business-cycle-dating-committee

Croushore (2011, p.81-82) and Mankiw and Shapiro (1986, p.22))

To show that our data revisions are driven by news, we test both criteria – the development of standard deviations and the correlation between revisions and errors.

Table 2 below reports standard deviation of revisions[12] for the flash (+45 days), revised flash (+65 days) and final (+100 days) release as well as revisions 6, 12, 18 and 24 months after the end of the report quarter. The Euro area real GDP and investment exhibit both consistent pattern of growing standard deviation from flash release to further revisions. Consumption variables seem to include noise, especially in the first estimates. Exports and imports are informative only for the estimates during the first year after the end of the report quarter and become noisy afterwards. The standard deviation of the US real GDP is continuously growing throughout the vintages which underlines the informativeness of series.

Table 2: Standard deviation of revisions within different vintages

Release date	45days	65days	100days	6 months	12 months	18 months	24 months
Y_{EA}	2.27	2.28	2.32	2.37	2.44	2.49	2.50
C	1.28	1.13	1.18	1.37	1.45	1.56	1.48
I	4.75	4.98	5.10	5.63	5.59	5.72	5.73
G	1.32	1.13	1.14	1.27	1.47	1.49	1.52
Ex	8.92	8.92	9.01	9.38	8.77	9.16	9.58
Im	8.11	8.11	8.30	8.58	8.13	8.23	8.16
Y_{US}	2.14	2.28	2.40	2.48	2.46	2.51	2.64

Note: we summarized firstly revisions for each variable 45 days, 65 days, 100 days, 6 months, 12 months, 18 months and 24 months after the end of the report quarter. Secondly we calculated standard deviation within each publication point for every variable.

The second test performed here disentangles whether revisions fulfill the orthogonality condition (3). To show this we calculated correlation between revisions and its revision errors for different release dates and performed standard test for significant correlation. The results are to be found in Table 3. The previous finding is reassured: for US real GDP, Euro area real GDP and investment as well as exports and imports we cannot reject the null of zero population correlation. Hence, the orthogonality is fulfilled. Unfortunately, the null hypothesis is rejected for the private and government consumption. Therefore, the uncertainty we observe in revisions of consumption variables originates in Eurostat's measurement errors and noise rather than in news.

[12] We calculated here standard deviation of the revisions, not of the revision errors.

Table 3: Correlation between the revision errors and revisions

Release date	45days	65days	6months	12months	18months	24months
Y_{EA}	0.19	0.23	-0.21	-0.26	-0.33	-0.29
	(0.05)	(0.02)	(0.11)	(0.07)	(0.04)	(0.06)
C	-0.68	-0.37	-0.53	-0.68	-0.77	-0.78
	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
I	0.04	0.01	-0.48	-0.39	-0.42	-0.41
	(0.38)	(0.47)	(0.01)	(0.03)	(0.02)	(0.02)
G	-0.58	-0.21	-0.46	-0.66	-0.69	-0.72
	(0.00)	(0.11)	(0.01)	(0.00)	(0.00)	(0.00)
Ex	0.1	0.41	-0.31	-0.14	-0.03	-0.18
	(0.21)	(0.00)	(0.05)	(0.19)	(0.41)	(0.14)
Im	-0.2	0.18	-0.22	0.05	0.02	0.06
	(0.21)	(0.06)	(0.1)	(0.36)	(0.44)	(0.33)
Y_{US}	0.19	-0.08	-0.28	-0.20	-0.24	-0.34
	(0.42)	(0.46)	(0.39)	(0.42)	(0.40)	(0.36)

Note: The p-values for the null hypothesis of no correlation are in brackets.

By the means of performed tests, we proved that our errors for major variables are revision errors and with every vintage Eurostat and FED eliminate forecast errors. As Euro area private and government consumption contain noise in revisions, we exclude these variables from the main uncertainty calculations throughout this paper.

4 Methodology

To analyze uncertainty of data revisions we base our findings on three types of methods: descriptive statistics of revision errors, different signal-to-noise-ratios and entropy measures for real macroeconomic variables.

4.1 Descriptive Statistics

The first method we applied to get an idea about the structure and magnitude of revision errors is descriptive statistics. We calculated recursive mean errors (ME), mean squared errors (MSE), mean absolute errors (MAE), root mean squared errors (RMSE), variance and standard deviation of revision errors for each growth rate and each variable.

Each vintage l consists of revision errors of different quarters t, though only one quarter can have its final release and per definition zero revision error during the same vintage. All other revision errors are non-zero since Eurostat revises each quarter almost at every vintage.

$$ME_l = \frac{1}{T}\Sigma_{t=1}^{T}(\hat{y}_t^L - \hat{y}_t^l) \tag{5}$$

$$MSE_l = \frac{1}{T}\Sigma_{t=1}^{T}(\hat{y}_t^L - \hat{y}_t^l)^2 \tag{6}$$

$$MAE_l = \frac{1}{T}\Sigma_{t=1}^{T} \mid (\hat{y}_t^L - \hat{y}_t^l) \mid \tag{7}$$

$$RMSE_l = \sqrt{\frac{1}{T}\Sigma_{t=1}^{T}(\hat{y}_t^L - \hat{y}_t^l)^2} \tag{8}$$

The focus of analysis are root mean squared errors for vintages of macroeconomic variables. Other results are available by the corresponding author on request.

4.2 Signal-To-Noise and Integrated-Signal-To-Noise Ratios

Another approach to measure the information content of real-time date goes back to "Signal-to-Noise" ratios (SNR). The signal-to-noise ratio is captured by a ratio of variances: The more information comes in, the lower the variance of revision, and the signal content improves compared to the noise level as measured by the variance of the final revision. Obviously, SNR approaches one in the limit.

$$SNR_l = 1 - \frac{1/T\sum(\hat{y}_t^L - \hat{y}_t^l)^2}{\sigma_L^2}, \tag{9}$$

where σ_L^2 denotes the variance of the final revision L.[13]

Oeller and Teterukovski (2007) propose an integrated SNR measure, the ISNR, to characterize the overall quality of data. For its computation they consider the mean squared error of signals in vintages l and $l+1$:

$$ISNR_L = \frac{1}{2}\sum_{l=0}^{L-1}(SNR_l + SNR_{l+1})\tau(l, l+1) \tag{10}$$

with $\tau(l, l+1)$ denoting the time interval between the vintages.
Both measures vary in between zero and one: complete ignorance about the final value up to the last revision on the one hand and a situation where the very first forecast (flash estimate) conveys all necessary information on the other hand.

[13] Oeller and Teterukovski (2007, p.207), Kholodilin and Siliverstovs (2009, p.3).

4.3 Entropy

The third method evaluates the information content of revisions in terms of entropy reduction, i.e. the reduction in uncertainty. The usage of this measure in economics goes back to Theil (1966, 1967) and Theil and Scholes (1967). The concept however originates in thermodynamics and statistical mechanics, and is closely related to the concept of information in communication theory and mathematical statistics (Patterson and Heravi, 1991, p.36).

The traditional entropy approach establishes H as a continuous distribution function F with a density function $f(x)$, defined in terms of normal distribution:

$$H(f) = -\int_{-\infty}^{+\infty} f(x)\log(f(x))dx \tag{11}$$

The means of the successive distributions, conditioned on the different stages in the forecasting process, are assumed to be constant (Theil, 1967; Patterson and Heravi, 1991). According to Patterson and Heravi (1991), the normal distribution is the one with the largest entropy, where the entropy is a linear function of the logarithm of the variance. A positive difference between the entropies of distribution conditioned on the different stages in the forecasting process implies a reduction of uncertainty attributable to the revision process (Patterson and Heravi, 1991, p.36). The decrease in entropy is usually referred to as "information gain" in the literature. Information gains are independent of time and represent the average vintage information gain across years and variables (Oeller and Teterukovski, 2007, p.210).

Vasicek (1976) proposed an entropy measure by dropping the restrictive normality assumption. Patterson and Heravi (1991, p.39) point out that a normal distribution assumption in general only holds if the variables are pooled, and restated the concept of Vasicek (1976):

$$H_{MT} = T^{-1}\sum_{t=1}^{T} \ln(\frac{T}{2M}\left[e^l_{(t+M)} - e^l_{(t-M)}\right]) \tag{12}$$

where $e^l_{(t)}$ is the ordered error such that $e^l_{(1)} \leqslant e^l_{(2)} \leqslant \cdots \leqslant e^l_{(T)}$ and M is a positive integer smaller than $T/2$, where T captures the number of observations in a vintage l. (Vasicek (1976, p.54-55), Patterson and Heravi (1991, p.39)).[14]

For the computation of the entropy measure we use the definition in equation (12). Hence, the entropy is the difference between ordered revision errors within a vintage. We enhance to the foregone entropy estimate and calculate an optimal value for M for each vintage separately, depending on the number of observations T within the vintage l. Following Vasicek (1976, p.58), we decide upon M according to the Table 4.

Table 4: Optimal Values for M

T	$T < 50$	$50 < T < 70$	$T > 70$
M	3	4	5

5 Results

This section presents the results of our revision analysis. As we previously detected noise in revisions of Euro area private and government consumption, we exclude these variables from the main discussion.[15] Along the way, we find additional support for the claim that data uncertainty rose in the past decade, notwithstanding the applied measure.

5.1 Euro Area Results

The measures of descriptive statistics capture primarily the magnitude of revisions. The results here are based on the root mean squared revision errors for all sample vintages. Hereby we are not making conclusions about data uncertainty, but rather concentrate on the intuition: if a variable exhibits high revision errors, than its flash release and probably even the final release does not capture enough information to match present economic situation.

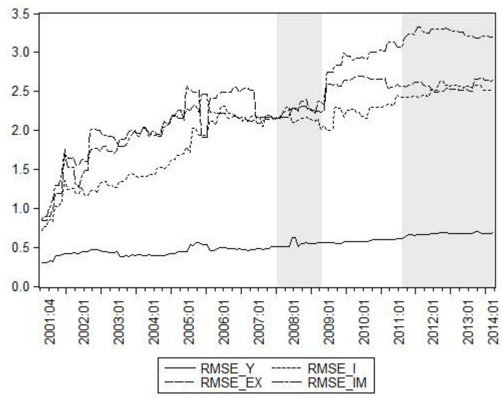
We find that revision errors have grown during the estimation period. The magnitude of revision errors differs between macroeconomic variables. GDP is less revised comparing with investment, exports and imports. The errors of the latter variables follow an upward trend.

Still, if we assume that the higher the root mean squared error of revisions, the higher the uncertainty is, this measure supports an argument of increasing uncertainty during the ”Great

[14] The notation of the original papers is changed to be consistent within this paper.
[15] The results of uncertainty measures calculations are available on request.

Recession".

Figure 1: Root Mean Squared Errors for the Euro area aggregates

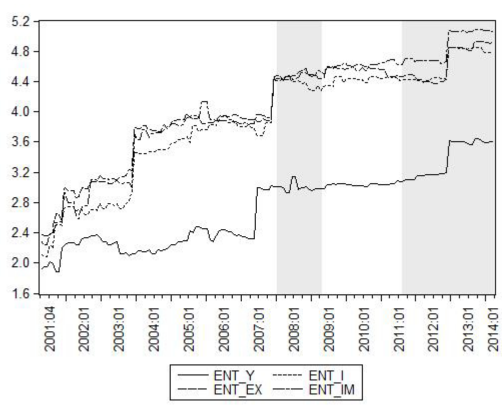


Note: The gray shaded area underlines recession

The main focus of data uncertainty section is on signal-to-noise ratios and entropy.

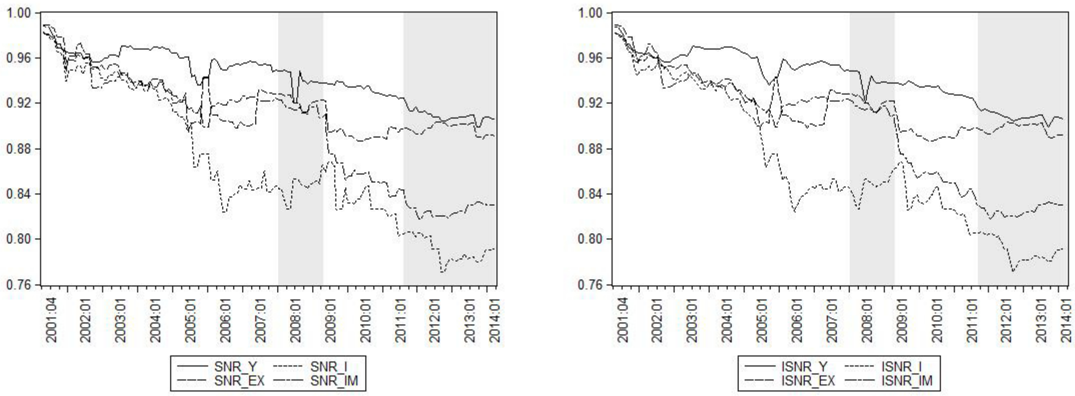
The entropy measure (12) is calculated as a distribution function of ordered revision errors and can be interpreted straightforward: the higher the entropy, the higher is the uncertainty in the data. All examined macroeconomic variables exhibit higher entropy and hence uncertainty levels within the last decade. The revision errors of exports, imports and investment are relatively high. Therefore the entropy measure for these aggregates is at the level higher as well, comparing with GDP.

Figure 2: Entropy measures for the Euro area aggregates



Note: The gray shaded area underlines recession

Figure 3: Signal-to-Noise Rations for the Euro area aggregates



(a) SNR (b) ISNR

Note: The gray shaded area underlines recession

Concerning signal-to-noise ratios we detect a clear downward trend. According to the definition of SNRs: the higher the ratio, the lower the uncertainty. Hence, uncertainty based on both SNR and ISNR has been rising throughout the vintages for all investigated variables.

Moreover, there are two structural breaks in signal-to-noise ratios and entropy measures. The first break can be explaned by the changes in the regional coverage of the Euro area. The second break eliminates if we apply an alternative deifinion of final release, as reported in section 5.3 further.

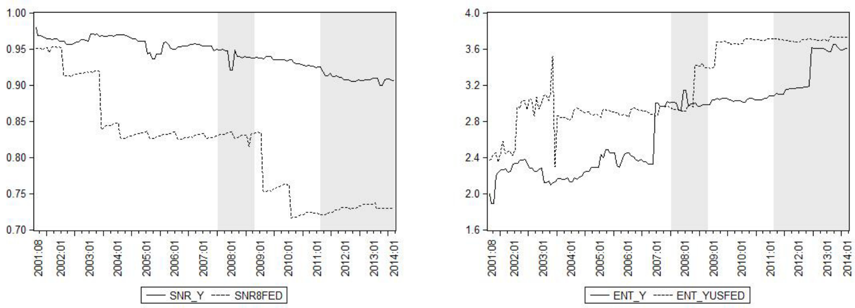
All applied methods detect that the uncertainty of the real GDP is lower than of its aggregates. This finding is probably due to the aggregation effect. The calculation of the real GDP includes two types of aggregation: firstly aggregation of the components and secondly aggregation throughout the Euro area countries.

The highest uncertainty consistently calculated with different measures is verified for investment.

5.2 US Results

Starting with descriptive statistics we observe that the root mean squared errors of the US revisions has been constantly growing, actually during the crisis at a higher level than the

Figure 4: Comparison between the Euro area and the US real GDP uncertainty estimates



(a) SNR (b) Entropy

Note: The gray shaded area underlines recession. SNR_Y and Ent_Y are the Euro area and SNR_YUSFED and Ent_YUSFED the US signal-to-noise and entropy measures resprectively.

Euro area errors. Therefore the result of signal-to-noise ratios is not surprising: the data uncertainty of US FED real GDP growth rate is higher than of the Eurostat Euro area aggregate. Moreover, the entropy measures of the US and Euro area real GDP seem to converge during the recent recession.

5.3 Robustness to Data Definitions

To demonstrate the robustness of our data uncertainty findings, we use in this section an alternative definition of final estimates. Eurostat announces the final estimate 100 days after the end of the quarter. In line with the US revision announcement policy we introduce revised final estimate as if it was announced eight quarters after the end of the report period. In terms of monthly revision structure the announcement is equivalent to $(t + 24)$ vintage. In terms of final release definition we follow here Aruoba (2008) and Giannone et al. (2012).

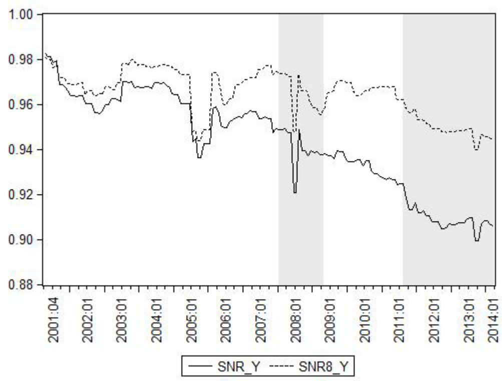
Figure 5 and 6 below give a comparison of revision errors calculation based on revised final definition. It can be clearly seen that the detected uncertainty trend is robust. The magnitude of uncertainty changes for the revision errors calculations with the revised final estimate only marginally. This finding indicates that the introduction of an official revised final would not significantly reduce the uncertainty and increase the accuracy of Eurostat data for all Euro area macroeconomic variables.[16]

For the US variables there is no difference between signal-to-noise ratios calculation for both

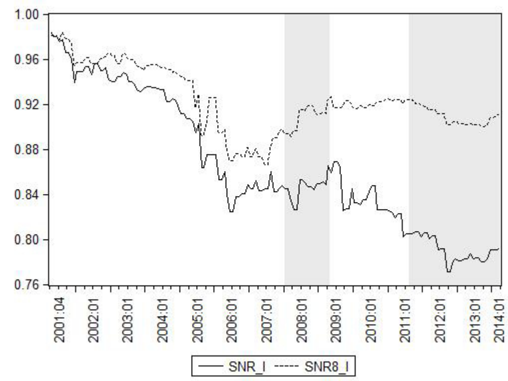
[16] Additionally we checked further definition of final: 36 months respectively three years after the end of report quarter. Though levels of uncertainty measures are lower than before, the consistent pattern of growing uncertainty is confirmed in this case as well.

final estimate definitions. The entropy measures exhibit the same pattern as the Euro area aggregates: the estimates of revised final differ marginally from the 100 days finals. The uncertainty trend stays robust.

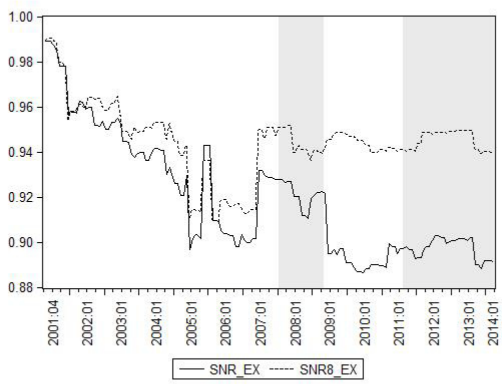
Figure 5: SNRs: Eurostat final estimate definition versus revised final ($t+8$) for the Euro area



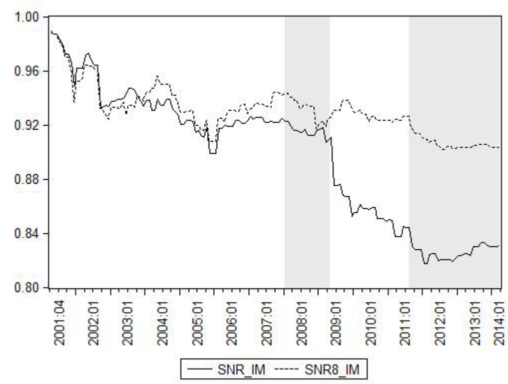
(a) Euro area real GDP



(b) Euro area Investment



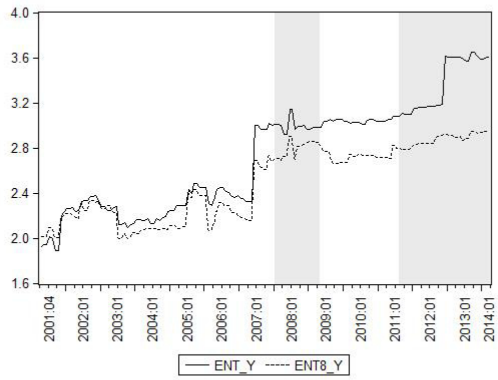
(c) Euro area Exports



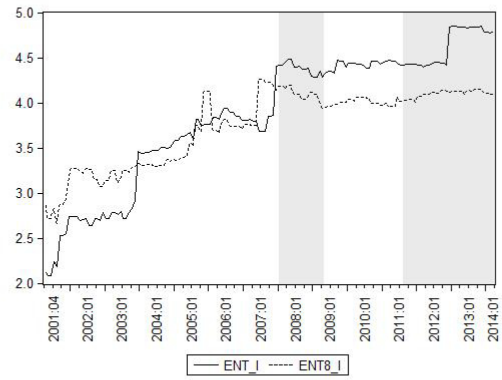
(d) Euro area Imports

Note: The gray shaded area underlines recession

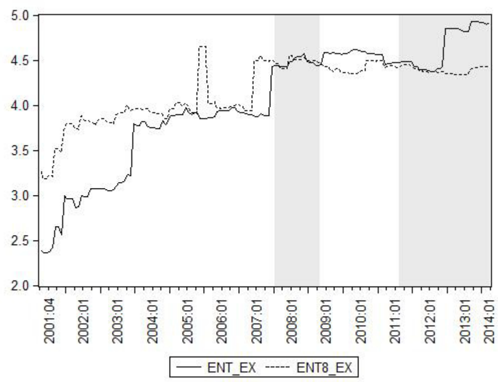
Figure 6: Entropy: Eurostat final estimate definition versus revised final $(t+8)$for the Euro area



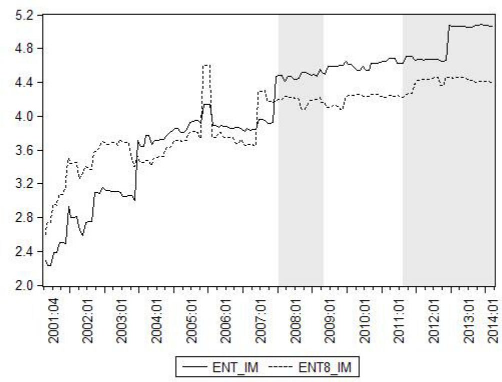
(a) Euro area real GDP



(b) Euro area Investment



(c) Euro area Exports



(d) Euro area Imports

Note: The gray shaded area underlines recession

On the whole the aforementioned upward uncertainty trend is detected for uncertainty in revisions both for the US and the Euro area. This conclusion is robust notwithstanding the definition of final estimates. Moreover our results are in line with the new macroeconomic uncertainty literature. However, this finding contradicts to the old revision studies, such as Kholodilin and Siliverstovs (2009) or Oeller and Teterukovski (2007) because of two main reasons. Firstly, the real data they used for uncertainty calculations ends during the “Great Moderation”, the period of low uncertainty levels in most countries. Secondly, these papers ignore the possible noisiness of revisions since they did not test for this issue explicitly.

In the next section we explore the relations between entropy measures and other popular uncertainty proxies for the US and the Euro area: new-based economic policy uncertainty and stock market volatility indices. The focus on entropy out of other herewith presented methods is due the fact that entropy is more intuitive: entropy captures the distribution of revision errors rather than summarizes MSEs within each vintage. Moreover we employ measures with $(t+8)$ definition of final estimate since it corresponds to the usual way to calculate revision errors.

6 Uncertainty Interactions

The recent research distinguishes between general macroeconomic uncertainty, traditionally measured by the first or second moment stock market volatility index and economic policy uncertainty proxied by the Baker et al. (2013) index. This paper adds another possible source of uncertainty which originates in the revision process - the entropy.

Furthermore there is a growing literature on uncertainty shocks and there influence on the real economy: Shields et al. (2005), Alexopoulos and Cohen (2009), Bloom (2009), Baker et al. (2013), Nodari (2013), Benati (2014), Caggiano et al. (2014a), Caggiano et al. (2014b), Leduc and Liu (2014), Mumtaz and Theodoridis (2014), Pesaran et al. (2014) among others. We do not analyze uncertainty shocks to other variables and leave this issue to further research. The scope of this section is to understand the relations between general uncertainty, captured by stock market volatility, economic policy uncertainty (new-based EPU indices by Baker et al.) and data uncertainty - previously computed entropy measures.

In the following we draw relations between popular proxies and entropy for the US and the Euro area by the means of correlation, Granger-causality and cointegration. Since we find unit roots in all series, to highlight these interactions we estimate two models: vector error-correction (VEC) and vector autoregressive (VAR) models.

Our first benchmark is the Economic Policy News Index. The Euro area news-based EPU index captures at equal shares the frequency of references to policy-related economic uncertainty in leading newspapers.[17]

The European EPU encompasses Germany, Spain, France, Italy and the UK. To make the index comparable with our Euro area estimates, we adjusted the index only for the Euro area countries and exclude the UK, using Baker-Bloom individual country data[18] and Eurostat indi-

[17] See for further details Baker et al. (2013, p.9-10) The computation of the EPU index for the US and the European countries differs.

[18] The media data includes two newspapers per European Union country.

vidual country real GDP shares of total real Euro area GDP. For the US estimations we include new-based EPU index.

Another traditional measure of uncertainty is stock market volatility. The EURO STOXX 50 volatility index (VSTOXX) captures variance across all options of a given time to expiry for the Euro area. VSTOXX is calculated on the basis of eight expiry months with a maximum time to expiry of two years. For the US economy Chicago Board Options Exchange (CBOE) calculates Market Volatility Index (VIX). CBOE measures market expectation of near term volatility conveyed by stock index (S&P 500) option prices.[19]

Unfortunately we can apply neither disagreement measures nor macroeconomic uncertainty like Jurado et al. (2015) proxy because it is not available for the Euro area.

Firstly, we examine whether there is any correlation between different uncertainty measures. Mean squared errors and entropy are positively correlated with the EPU index, while for signal-to-noise ratios we detect a negative relation to the EPU index. The negative correlation is explained by the definition of ratios. Declining SNR and ISNR underline rising uncertainty, and vice versa. The US and the Euro area EPU indices both exhibit correlation of 0.6 to the entropy measures. Though both VSTOXX and VIX follow the same trends, it is hardly correlated with our measures.[20] These correlation coefficients are significant: for null hypothesis of no correlation cannot be rejected for the stock market and our measures series, the exhibited correlation to EPU index is significantly different from zero. Nevertheless these results have to be interpreted with caution because the series we deal here with are non-stationary.

Table 5: Correlation between the entropy measures, EPU news based indices and stock market volatility indices for the US and the Euro area

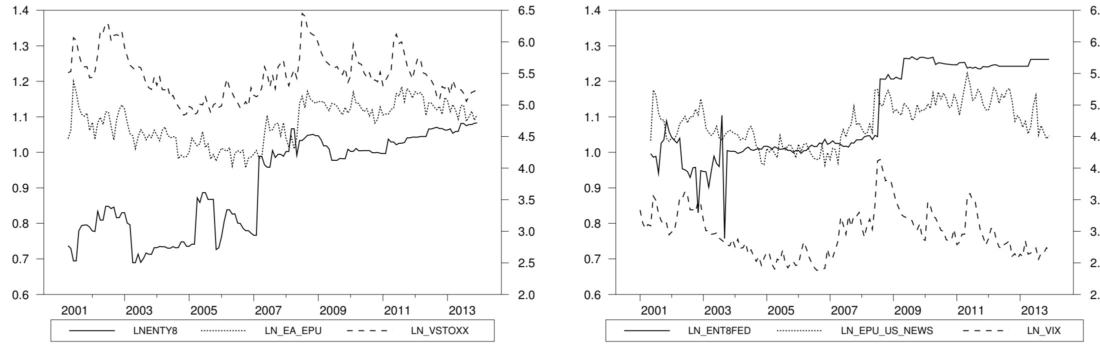
	Entropy EA	Entropy US
EPU	0.6	0.6
VSTOXX/VIX	0.2	0.1

Note: all variables are in logarithms.

Secondly, Figure 7 below demonstrates that the series are non-stationary and visually not cointegrated, especially stock market volatility. We apply Engle and Granger (1987) and Johansen (1988) co-integration tests to uncertainty measures pairwise: entropy versus EPU indices and entropy versus VSTOXX or VIX respectively. The model with the constant term is restricted to be in the cointegrating vector.[21] Engle and Granger cointegration tests reject the null of

[19] Further details are to be found in appendix A.
[20] The detailed correlation table for the euro area you will find on table 11.
[21] In this case, there are no linear trends in the data. The only deterministic component in the model is the intercept

Figure 7: Uncertainty measures for the US and the Euro Area: Entropy Measures, news-based Economic Policy Indeces and Stock Market Volatility Indeces



(a) Euro Area

(b) US

Note: LNENTY8, LN_EA_EPU and LN_VSTOXX are logarithms of the Euro area entropy, EPU and VSTOXX respectively. LNENT8FED, LN_EPU_US_NEWS and LN_VIX are logarithms of the US entropy, EPU and VSTOXX respectively.

no cointegration only for entropy and EPU index for the Euro area and the US. According to the Johansen methodology we find at least one cointegration rank for all US and Euro area variable pairs.[22] Further, the estimation of VECM did not deliver significant insights in the relations between the variables. Therefore we prefer the VAR model in first differences with two lags[23].

Granger-causality tests for the first difference VAR with two lags[24] show in Table 6 similar tendencies for both regions between uncertainty measures. There is a significant causality from the Euro area EPU index to entropy. We do not find Granger-causal connection between other variables.

Table 6: Results of Granger causality tests

The null hypothesis	Test statistics
Euro area Entropy does not Granger cause EPU index	F=0.85
Euro area EPU index does not Granger cause Entropy	F=$4.58^{\star}$
Euro area Entropy does not Granger cause VSTOXX	F=0.28
Euro area VSTOXX does not Granger cause Entropy	F=0.88
US Entropy Granger does not cause EPU index	F=0.92
US EPU index does not Granger cause Entropy	F=0.93
US Entropy does not Granger cause VIX	F=0.57
US VIX does not Granger cause Entropy	F=0.10

Note: The significance of test statistics is given by the number of asterisks: *, ** and *** for 10%, 5% and 1% significance level respectively.

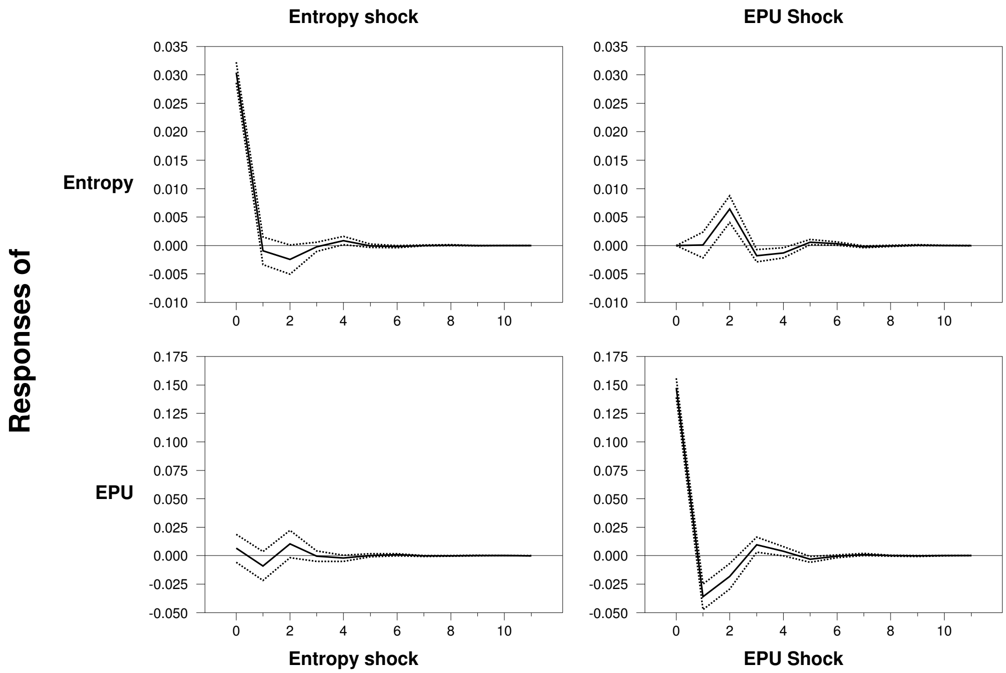
of the cointegrating vector, implying that the equilibrium mean is different from zero. (Juselius, 2006, p.100)

[22]The results of cointegration tests are to find in appendix Table 12.

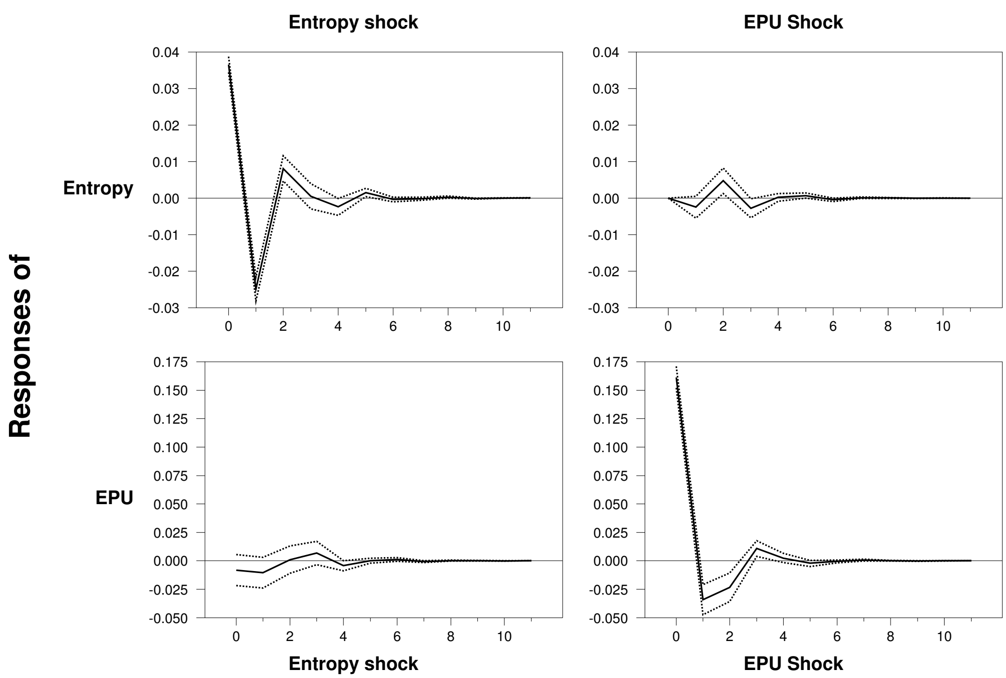
[23]The two lags specification is chosen according to Akaike information criterion.

[24]We estimate two VARs for each region separately.

Figure 8: Impulse Responses of the VARs



(a) Euro Area



(b) US

Note: All variables are in differentiated logarithms. VARs has two lags.

Figure 8 shows the impulse responses of the first-difference-VARs estimated with EPU and Entropy for the US and the Euro area. We see qualitatively similar effect. Economic policy uncertainty shock has a lagged positive impact on the entropy: data uncertainty increases with a lag in case of a policy uncertainty shock. The examination of forecast error variance decomposition underlines that the entropy measures do not have any explanation effect of the variance of the EPU, as shown in the Tables 7 and 8. The effect is more pronounced in the other direction: almost 5% of entropy variance can be explained by the EPU shock, for the US about 2% is explained by the shock. This result goes in line with the Granger causality tests: there is verifiable relation between the EPU index and entropy in the Euro area.

Table 7: Forecast error variance decompostion of entropy series

Horizons	EA Ent	EA EPU	US Ent	US EPU
6	95.21	4.79	98.20	1.80
12	95.19	4.81	98.19	1.81
24	95.19	4.81	98.19	1.81

Table 8: Forecast error variance decompostion of EPU series

Horizons	EA Ent	EA EPU	US Ent	US EPU
6	0.99	99.01	0.88	99.12
12	0.99	99.01	0.88	99.12
24	0.99	99.01	0.88	99.12

7 Conclusion

Prior work has documented increased uncertainty in terms of different uncertainty proxies[25]; Baker et al. (2013), for instance, applied the news-based economic policy uncertainty index, another popular proxies are stock market volatility index or Scotti's "surprise" index. However, most of uncertainty measurements are made based on US data, especially on the US SPF forecast probability distribution. For the Euro area there is less research concerning uncertainty, the focus of available papers is again on SPF data. In this study we analyzed how the information content for the Euro area and the US has changed over time using Eurostat and FED real time data. This paper adds to the uncertainty literature and focuses on data uncertainty in terms of real gross domestic product and its component revisions as obe possible component of the overall economic uncertainty. We showed that apart from general uncertainty measured typically by stock market volatility and economic policy uncertainty, data uncertainty has to be

[25] See i.e. Bloom (2009); Bloom et al. (2013); Bloom (2014); Baker et al. (2014); Scotti (2013); Jurado et al. (2014).

taken into account.

Our study measured data uncertainty applying three methods: descriptive statistics, signal-to-noise ratios and entropy. We found that data uncertainty of macroeconomic variables in the Euro area and the US has become higher within the last decade. This finding extends Bloom (2014) stylized fact on uncertainty based on the US data, who postulated that during the recession uncertainty is much higher than within the stability and prosperity period. We can luckily transfer this stylized fact to the revisions. Uncertainty has been continuously growing with the last decade for both regions. The increase is even dramatic during the recession for all Euro area macroeconomic variables, comparing with reference uncertainty proxies, which indicates relief of uncertainty.

Most notably, the uncertainty increase of the Euro area real GDP is weaker than for its aggregates, probably because of the double aggregation effect. In addition, investment tends to be highly uncertain. According to signal-to-noise ratios, private and government consumption exhibited high uncertainty level and contradicted entropy measure. Unfortunately revisions of these variables are correlated with errors and therefore contain noise instead of new information. Revisions of all other variables fulfill orthogonality condition, validating uncertainty calculations.

After establishing an entropy measure of data uncertainty, we analysed its interactions with other recently discussed measures such as general uncertainty (VSTOXX and VIX) and economic policy uncertainty indices for both regions. Our results underline that data has a publication lag, which is consistent with findings of real time literature. Moreover, there is (one-way) Granger causal relation between economic policy uncertainty and entropy in the Euro area. EPU shocks from the US and the Euro area seem to have lagged positive influence on the entropy: economic policy uncertainty shock generates increase in data uncertainty.

Hence, data uncertainty is an alternative channel of uncertainty and has to be included in the estimation models along with traditional uncertainty macroeconomic or economic policy uncertainty proxies.

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A Data Download Information

Table 9: Eurostat Download Information

Eurostat name	Short name	
Euro area (moving concept in the Real Time database context) Gross domestic product at market price Chain linked volumes - Euro	Gross Domestic Product	Y_{EA}
Euro area (moving concept in the Real Time database context) Final Consumption of Households and NPISH's (private consumption)[26] Chain linked volumes - Euro	Consumption	C
Euro area (moving concept in the Real Time database context) Gross Fixed Capital Formation Chain linked volumes - Euro	Investment	I
Euro area (moving concept in the Real Time database context) Final Consumption of General Government Chain linked volumes - Euro	Government Consumption	G
Euro area (moving concept in the Real Time database context) Exports of Goods and Services Chain linked volumes - Euro	Exports	Ex
Euro area (moving concept in the Real Time database context) Imports of Goods and Services Chain linked volumes - Euro	Imports	Im

In the recent version of the paper the Eurostat data was updated on April 29^{th} 2014.
http://sdw.ecb.europa.eu/browseExplanation.do?node=4843526.
Further information concerning the variables can be found in EUROSTAT (2013).

Table 10: Further Data Download Information

Federal Reserve Bank of Philadelphia Real GNP/GDP (ROUTPUT) Billions of real dollars, seasonally adjusted http://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/data-files/ROUTPUT Download on 08.22.2014	US FED GDP or Y_{US}
EURO STOXX 50 volatility index http://www.stoxx.com/index.html. Download on 05.27.2014	VSTOXX
Chicago Board Options Exchange Market Volatility Index http://research.stlouisfed.org/fred2/series/VIXCLS. Download on 09.12.2014	VIX
Economic Policy Uncertainty Index for the US and Euro area Source: Scott Baker, Nicholas Bloom and Steven J. Davis US: http://www.policyuncertainty.com/us_monthly.html EA: http://www.policyuncertainty.com/europe_monthly.html Download on 09.12.2014	EPU

B Additional Tables

Table 11: Correlation between the Euro area EPU news based index, VSTOXX and different uncertainty measures

	LN_EA_EPU	LN_VSTOXX
LN_EA_EPU	1.00	0.62
LN_VSTOXX	0.62	1.00
RMSE_Y	0.54	0.01
RMSE_C	0.40	-0.02
RMSE_I	0.27	-0.20
RMSE_G	0.19	-0.12
RMSE_EX	0.18	-0.24
RMSE_IM	0.48	-0.10
AVERAGE	**0.34**	**-0.11**
SNR_Y	-0.55	0.00
SNR_C	-0.43	0.01
SNR_I	-0.32	0.18
SNR_G	-0.22	0.12
SNR_EX	-0.22	0.24
SNR_IM	-0.53	0.08
AVERAGE	**-0.38**	**0.11**
ENT_Y	0.54	0.04
ENT_C	0.42	-0.11
ENT_I	0.34	-0.17
ENT_G	0.36	-0.13
ENT_EX	0.33	-0.16
ENT_IM	0.37	-0.15
AVERAGE	**0.39**	**-0.11**

Table 12: Results of Engle and Granger and Johansen cointegration tests

Test	H_0	EA Ent and EPU	EA Ent and VSTOXX	US Ent and EPU	US Ent and VIX
Engle and Granger	$r = 0$	$-3.07^{\star}$	-1.52	$3.51^{\star}$	2.53
Johansen: λ_{trace}	$r \leq 1$	18.22	11.56	18.24	12.13

Note: The significance of test statistics is given by the number of asterisks: *, ** and *** for 10%, 5% and 1% significance level respectively.