Universität Innsbruck

Time-Varying Uncertainty and Business Cycles

An Inquiry into the Theory, Measurement and Macroeconomic Effects of Uncertainty

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Univ.-Prof. Dr. Johann Scharler

Department of Economics
Faculty of Economics and Statistics
Leopold-Franzens-Universität Innsbruck

by
Mag. Marcel A. Kropp

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To my Mum.

What I've written when handing in the diploma thesis for my first degree still holds more than ever:

My family has been my strongest support in all my life. I especially want to express my gratitude to my dear uncle Dr. med. Farshid Mavaddat, my cousins Dr. Paik Saber and Neisan Saber and my aunt Mahshid Mavaddat.
Most of all I want to thank my Mum, Dorrie Mavaddat, who has always been there for me and supported and helped my in all my ventures. It is due to her that I stand where I am today.

Innsbruck, July 2018

Abstract

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

Zusammenfassung

Dies hier ist ein Blindtext zum Testen von Textausgaben. Wer diesen Text liest, ist selbst schuld. Der Text gibt lediglich den Grauwert der Schrift an. Ist das wirklich so? Ist es gleichgültig, ob ich schreibe: „Dies ist ein Blindtext“ oder „Huardest gefburn“? Kjift – mitnichten! Ein Blindtext bietet mir wichtige Informationen. An ihm messe ich die Lesbarkeit einer Schrift, ihre Anmutung, wie harmonisch die Figuren zueinander stehen und prüfe, wie breit oder schmal sie läuft. Ein Blindtext sollte möglichst viele verschiedene Buchstaben enthalten und in der Originalsprache gesetzt sein. Er muss keinen Sinn ergeben, sollte aber lesbar sein. Fremdsprachige Texte wie „Lorem ipsum“ dienen nicht dem eigentlichen Zweck, da sie eine falsche Anmutung vermitteln.

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1. Introduction

It can be commonly postulated that being faced with uncertainty is a state inherent to life's existence and in every aspect a natural part of our complex world.
Focussing on *economic* uncertainty, an investor being concerned about the performance of her assets, an employee being worried about future income streams during retirement or at all still having a job one year from now or a business continuously defending its position on the market are just a few examples of individuals or a collective being exposed to uncertainty in every-day life. Many of these risks/uncertainties[1] have given rise to institutions and entire industries as an integral part of today's modern economies: sophisticated financial markets (with their risk-transformation-function being a pivotal element besides the purpose to raise capital) and the finance and insurance industry would not exist (or albeit in a different form) if it was not for the existence of uncertainty. On the academic front, ever more complex models promise remedy to make exposures to uncertainty and foresight calculable and/or manageable.

Going beyond these exemplary scenarios where economic agents seem to take into account some sort of probabilistic assessment of the future turn of events, on an aggregate level specific (tail) events can cause (economic or political) uncertainty to ultimately feed into the micro-level (firms and households) in a potentially damaging way, being rather perceived as exogenous shocks (i.e., outside of one's own area of influence) than part of a known probabilistic state space.

[1] Note that we are currently still using these terms interchangeably but will give a brief overview of the discussion and their subtle differences in the literature below.

As aptly formulated by Nicholas Bloom[2], after the Great Recession, the subsequent turmoil in the Eurozone's sovereign debt markets and the Arab Spring being just a few examples, the most recent major political events[3] of Brexit, Trump's election in the US, and a seeming worsening of the relationship between forces of the West and East have intensified concerns about uncertainty. Assessments from the Federal Open Market Committee (2009)[4] and the International Monetary Fund (IMF, 2012, 2013)[5], for example, suggest how multilayered uncertainty can be by referring to how factors such as "[...] U.S. and European fiscal, regulatory, and monetary policies [have] contributed to a steep economic decline in 2008-2009 and slow recoveries afterward." (Baker et al., 2015, p.1594)

On a high level, Dequech (2000) identifies four basic social practices in today's societies that have a stabilizing effect on the coexistence in our (as he calls it) *economic reality*: (1) legal contracts (that reduce the uncertainty of future values of nominal variables), (2) the 'State' which enforces legal contracts in case one party to a contract would decide to not fulfill its obligations, (3) Market-Makers (a very prominent example being central banks in their roles as lenders of last resort), and lastly, (4) informal institutions including conventions like 'socially shared and/or prescribed standards of thought and behavior'. Together these features improve subjective and objective uncertainty but can obviously not completely eliminate it.

Although we do not want to roll up the subject from a philosophical (or even religious) perspective, whoever analyses *uncertainty* and its underlying

[2]Bloom is part of a larger group of contributors to the most recent macroeconomic literature that has started to systematically disentangle the effects of uncertainty both theoretically and empirically.

[3]One could potentially also call them 'shocks'.

[4]"Widespread reports from business contacts noted that uncertainties about health-care, tax, and environmental policies were adding to businesses' reluctance to commit to higher capital spending" (Federal Open Market Committee, 2009).

[5]"More seems to be at work, however [...] - namely, a general feeling of uncertainty'. Assessing the precise nature and effects of this uncertainty is essential, but [...] not easy. [...] Uncertainty appears more diffus, more Knightian in nature." (IMF, 2012). In IMF (2013) the authors dedicated a whole section (pp. 70-67) to the study of the effects of uncertainty, stating that "[a] common view is that high uncertainty in general, and high policy uncertainty more specifically, has held back global investment and output growth in the past two years." (IMF, 2013, p. 70).

meaning in the literature hoping to clearly differentiate it from related concepts such as *risk* or *ambiguity*, will quickly realize that an unambiguous definition is not straightforward. Confining ourselves to economics only, there is a vast array of literature starting at the beginning of the 20th century that refers to these concepts in different schools of thought that at their core do have a philosophical component to them. Different parlance within the profession which even causes similar concepts to be named differently or the same term being used with a different meaning additionally complicates matters.

While a thorough discussion of every aspect of the related concepts is beyond the scope of this work, we still want to give a brief overview of a few insights by referring to a few selecting writings:

Dow (2016) tries to clarify the difference between the mainstream and Keynesian[6] understanding of *uncertainty*[7], its distinction from *risk* and the resulting theoretical implications[8]. According to her assessment, in the traditional mainstream analysis within a Bayesian framework most knowledge is viewed as known or known to be stochastic in some form (called *risk*), meaning that the state space is known and numerical probabilities can be assigned. Under this approach, mainstream traditional macroeconomic models give only very limited room, if any, to *uncertainty* as a state of absence of such probabilities in the form of exogenous sources of shocks[9].

Read from this dualistic mainstream perspective, Dow (2016) asserts that Keynes's standpoint was also for a long time interpreted in a dualistic way, albeit flipped in the sense that only in special circumstances, knowledge (here referred to as *risk*) could be treated as certain and (fundamental) uncertainty was regarded as the general case (see the introduction in Keynes, 1921). This

[6]Keynes and Knight are often-times regarded as the two prominent figures that introduced the concept of *fundamental uncertainty* into the economic sciences.

[7]Dow (2016) also makes account to von Mises, Hayek and Shackle who have also dealt with uncertainty in their works but focusses on Keynes's views on fundamental uncertainty arguing for it to be the most developed and philosophically-grounded counterpoint to the mainstream theory.

[8]Note that there are also schools that reject the distinction between *uncertainty* and *risk* altogether (e.g., Savage, 1954).

[9]Dequech (2000, p. 43) refers to some economists partly neglecting fundamental uncertainty following the argument that it might lead to 'theoretical nihilism' (see e.g., Coddington, 1982).

dualistic interpretation was seemingly reinforced by Keynes's reflections on long-term expectations (Keynes, 1937, p. 214/214): "About [uncertainty] there is no scientific basis on which to form any calculable probability whatever. We simply do not know."

But Dow (2016) clarifies that in the meantime it is well-established that Keynes did not give up on scientific knowledge (i.e., did not advocate nihilism) by giving so much weight to uncertainty but that his view on uncertainty is rather multidimensional and consists of various degrees. As an advocate of this view, Dequech (2000) argues that Keynes referred to both ambiguity in his early writings (Keynes, 1921)[10] and fundamental uncertainty in his later ones (Keynes, 1937) and that simply speaking of Keynesian uncertainty may actually be too vague in most circumstances.

Camerer and Weber (1992, p. 330) describe ambiguity as "uncertainty about probability, created by missing information that is relevant and could be known". Dequech (2011, p. 623) states that while usually the decision-maker under ambiguity cannot reliably assess the probability of each event, she usually knows all possible events (or it is at least "predetermined or knowable ex ante") while the case of fundamental uncertainty "[...] is characterized by the possibility of creativity and non-predetermined structural change". So under this concept and "[w]ithin the bounds imposed by natural laws, the list of possible events is not predetermined or knowable ex ante [...] as *the future is yet to be created*[11]" (Dequech, 2011, p. 623).[12]

With regard to fundamental uncertainty, Dequech (2000) mentions technological or managerial innovations as examples of human creativity that can disrupt our realities which is closely connected to the process of creative destruction of Schumpeter (1942). Unpredictable structural changes (e.g. historical changes) to our economic reality on the other hand are more typically politi-

[10] According to interpreters, in terms of Keynes (1921), for both ambiguity and fundamental uncertainty there is no basis for the assignment of point, numerical probabilities (Dequech, 2000).

[11] Italics added.

[12] Dequech (2000) sees the work of Shackle (2017) as advocating this argument.

cal, social or cultural disruptions where institutions and technological change play a key-role. Interestingly, the capitalist system as we know it is regarded as endogenously causing uncertainty due to competing economic actors and decision-makers innovating in search for extra profits (see Kregel, 1987)[13].

Coming back to the mainstream view, while the crisis and subsequent Great Recession has triggered a rethinking of the mainstream approach to uncertainty by emphasizing "institutional impediments to information access (asymmetric information)" (Dow, 2016, p. 8), degrees of uncertainty were only gradually added to the picture: the term 'ambiguity' was acquired as well (also following Camerer and Weber, 1992, p. 330) to account for these various degrees of uncertainty while 'unknown unknowns' (i.e. unimaginable events or 'black swans' as dubbed by Taleb, 2008) would have to be seen as *'knowable unknowns'* to still be consistent with the Bayesian framework. The term 'ambiguity' is thereby introduced as falling either into the category of risk or uncertainty depending on the ability to quantify higher-order probabilities.

Trying to establish a typology within the introduced terms, Dequech (2011) sets up three dimensions along which he classifies relevant concepts[14]:

1. between substantive and procedural uncertainty:[15]
2. between weak and strong uncertainty:[16]
   weak uncertainty is then further subdivided into *Knightian risk* (see Knight (1921); often simply called 'situations of risk' where agents are faced with objective probabilities, either a priori or statistical probabilities

[13] Despite of the above remarks, Keynes' notion of uncertainty as described in Keynes (1921) and its connection to Keynes (1937) has been subject to much controversy due to differing interpretations (Dequech, 2000).

[14] Apart from this classification we do not discuss any further interrelationships between the various concepts.

[15] Proposed by Dosi and Egidi (1991, p. 145) whereby substantive uncertainty results from the "lack of all the information which would be necessary to make decisions with certain outcomes" and procedural uncertainty from "limitations on the computational cognitive capabilities of the [respective] agents to pursue unambiguously their objectives, given [...] available information" in a complex decision problem.

[16] Whereby under weak uncertainty "[...] an agent can form [...] a unique, additive and fully reliable probability distribution" based on relevant and good-quality information and strong uncertainty consequently "[...] by the absence of such a distribution" (Dequech, 2011, p. 622/623).

(i.e., relative frequencies) and *Savage's uncertainty* (see Savage (1954); who introduced a full theory of 'personal probability' where *personal* belief governs probabilities, based on prior groundbreaking work of Ramsey (1926)[17] and de Finetti (1937));

3. between ambiguity and fundamental uncertainty.[18]

Abstracting from the (philosophical) considerations above, the question arises as to whether there is any consent in the literature about whether uncertainty can be quantified and, if so, how this could be achieved? And once having a meaningful measure of unertainty, what *real* effect, if any, does it exert on business cycles?

Within the past ten years and largely triggered by a seminal work by Bloom (2009)[19], macroeconomists have intensively started studying this question more intensively than ever before. At a first glance, as summarized by Jurado et al. (2015, p. 1177), partial equilibrium analyses to date suggest that increased levels of uncertainty "[...] can depress hiring, investment, or consumption if agents are subject to fixed costs or partial irreversibilities (a 'real options' effect), if agents are risk averse (a 'precautionary savings' effect), or if financial constraints tighten in response to higher uncertainty (a 'financial frictions' effect)."

While these effects have been identified by and large in the literature, the timing, extent and causality of effects remain hotly debated not least because of various uncertainty measures being used that try to quantify a decisive factor: unobservable, time-varying aggregate economic uncertainty.

The remainder of this thesis is organized as follows. Section 2 explores alternative uncertainty measures, their time-series properties as well as some

[17]Written "in opposition" to Keynes (1921).

[18]Which are two types of strong and substantive uncertainty (Dequech, 2000).

[19]Bloom's contribution triggered a wave of studies that challenged the effects that he had reported in his initial publication in Bloom (2009). We will come back to this multiple times throughout this text, especially in Section **??**.

'stylized facts' on uncertainty, Section 3 briefly reviews the related literature triggered by the seminal work of Bloom (2009), Section 4 is dedicated to the empirical analysis using data for the US and starting from a replication of the benchmark model of Bloom (2009) contrasts the isolated effects based on various uncertainty measures, samples and estimation techniques (VARs and the local projection method following Jordà, 2005), and Section 5 summarizes and concludes.

Additional details and results are outsourced to Appendix B including information on the data and the entire code and Appendix A including information on the differences between VARs and the local projection method by Jordà (2005).

2. A Closer Look At Uncertainty

Note to self:

- The IMF Working Paper (Measuring Global and Country-Specific Uncertainty) is a very helpful resource because the introduction to their paper is very insightful with lots of useful information about the current state of research in this respect!

Studies that try to explain the impact of uncertainty, if any, on aggregate economic fluctuations[1] not only differ with respect to econometric specifications (which we will examine in Section 4) but also to the deployed *uncertainty measure* itself. In fact, there is currently a very active and dedicated branch of the literature that tries to answer that one question: How can we best and most objectively measure uncertainty? And out of the suggested uncertainty measures to date, which one is the preferred one?

In what follows below we, first, want to review a selection[2] of uncertainty measures that have been used/suggested in the literature to date including their pros and cons and, second, investigate some of their time series properties to get a feeling of their similarities as well as discrepancies.

2.1. Measuring Macroeconomic Uncertainty

Mention the following: Uncertainty measures are either aggregate proxies or proxies derived from micro-data. Somehow this sentence must be included!

[1]Note that Section 3 will review these studies in more detail.

[2]We have decided to restrain ourselves to *four* measures which are among the most commented-on in the literature and which we examine in more detail for the purpose of this thesis.

Various uncertainty measures exist (and not *the one* measure) because the stochastic process which we commonly call 'uncertainty' is unobservable. Jurado et al. (2015, p. 1182) emphasize that "[t]he literature on measuring uncertainty is still in its infancy" and so far existing research has popularized various proxies or indicators of uncertainty.

The lack of an objective uncertainty measure hence poses a serious challenge to studies trying to quantify its macroeconomic effects: they have to come up with a reasonable uncertainty measure in the first place. Jurado et al. (2015, p. 1178) explain that "[w]hile most of the [above mentioned] measures have the advantage of being directly observable, their adequacy as proxies for uncertainty depends on how strongly they are correlated with this latent stochastic process [i.e., with unobservable uncertainty]".

Besides creating their own measure of economic uncertainty, Orlik and Veldkamp (2014) describe commonly used proxies of uncertainty by means of the following taxonomy and refer to selected works along the way[3]:

- **Forecast Dispersion:** add detailed description!
- **Mean-Squared Forecast Error:** add detailed description!
- **Volatility and Confidence Measures**, where we find three alternative approaches:
  - 'finance-based' - measures, assuming that financial volatility is a suitable indicator for aggregate macroeconomic uncertainty:
    - the traditional measure of uncertainty is the implied (e.g., the market volatility indices VIX/VXO) or realized volatility of stock market returns; based on these measures, Bloom (2009) constructs his shock-measure (henceforth called 'Bloom-shock'; see Section 2.1.1 below)
  - 'forecast-based'[4] - measures that rely either on an economy's pre-

[3]Note that we have slightly extended the original taxonomy of Orlik and Veldkamp (2014) by mixing it with Bontempi et al. (2016)'s taxonomy. Only the measures that link to a dedicated section will examined in more detail below.

[4]Note to self: we still have to fit 'the cross-sectional dispersion of firm profits, stock

dictability or the measurement of discrepancies between professional forecasts assuming that impeded predictability or a large dispersion between forecasts, respectively, points at a more uncertain economy:

  * cross-sectional dispersion measures of subjective business or consumer confidence (direction or point forecasts) based on survey data assuming that "[...] this inter-personal dispersion measure is an acceptable proxy for the average dispersion of intra-personal uncertainty" (Ozturk and Sheng, 2017, p. 4): e.g., Bachmann et al. (2013) use survey data in their analysis (note to self: briefly mention their used measures), Jurado et al. (2015) also mention analysts' forecasts (as e.g., used by D'Amico and Orphanides); Leduc and Liu (2016) instead use a measure constructed using data from the Thomson Reuters/Uniersity of Michigan Surveys of Consumers (henceforth called MSoC-index; see Section 2.1.2 below)
  * Jurado et al. (2015) construct a (as Orlik and Veldkamp (2014) call it) 'state-of-the-art' macro uncertainty index (henceforth called 'macro uncertainty index' see Section 2.1.4) that reflects uncertainty around objective statistical forecasts

- 'news-based' - approaches that measure the degree of uncertainty by extracting the frequency with which specific words appear in newspaper articles, assuming that journalists are able to assess emerging uncertainty [5]:
  * Alexopoulos and Cohen (2009) construct a news-based index derived from the number of New York Times' articles on uncertainty and economic activity,
  * Baker et al. (2015) construct an index of economic policy uncertainty (EPU) for a number of countries (including the United States) by searching for uncertainty-related keywords within a pool of widely read country-specific newspapers (henceforth

returns, or productivity' somewhere into our taxonomy!

[5] Note that this approach is similar to the narrative analysis used by Romer and Romer (2004), Romer and Romer (2017) or Ramey (2009).

called 'EPU index'; see Section 2.1.3),
in a similar vein, Moore (2016) constructs an index of economic uncertainty for Australia,

* inspired by classical 'news-based' - approaches, Bontempi et al. (2016) and Castelnuovo and Tran (2017) construct 'Google Trends Uncertainty' indices (they call their index GT- and GTU-index, respectively) based on freely accessible, real time Google Trends data; thereby the focus is shifted from journalists drawing the public's attention to specific topics to the public's individual Internet searches

We will discuss a few of these measures in turn.

2.1.1. A Finance-Based Measure: VXO/Stock-Market Volatility

Within the range of finance-based measures stock market volatility is a widely used proxy for uncertainty.[6] In particular, it is *forward-looking* measures of stock market returns/volatility that are especially useful which can be constructed from the *implied volatility* of stock options. In the case of the U.S. the VXO[7] is such a measure being available, however, only as of 1986. To cater for this limited time-frame, e.g., Bloom (2009) constructs a continuous time-series as shown in Figure 1 starting in July 1962 consisting of two components: (i) VXO-data for the period where data is available (i.e., as of 1986) and (ii) actual realized monthly volatilities for the period pre-1986 calculated as the within-month standard deviation of daily percentage changes of the S&P500 (normalized to the same mean and variance as the VXO index for when the

[6]In the literature it especially raised to popularity due to Bloom (2009). Details follow in the following chapters.

[7]The VXO-index is calculated and made available by the Chicago Board Options Exchange (CBOE) and covers publicly traded firms only (covering approximately 1/3 of private employment; see Davis et al., 2006) and reflects the market's expected implied volatility based on S&P100 options over a 30-day look-ahead period. Note that the VIX introduced as of 2003 instead is based on prices of S&P500 options. For more details see Chicago Board Options Exchange (2009) for a discussion of the VIX including references to the VXO.

two series overlap in Bloom's design, i.e., from 1986 - 2003).[8,9]

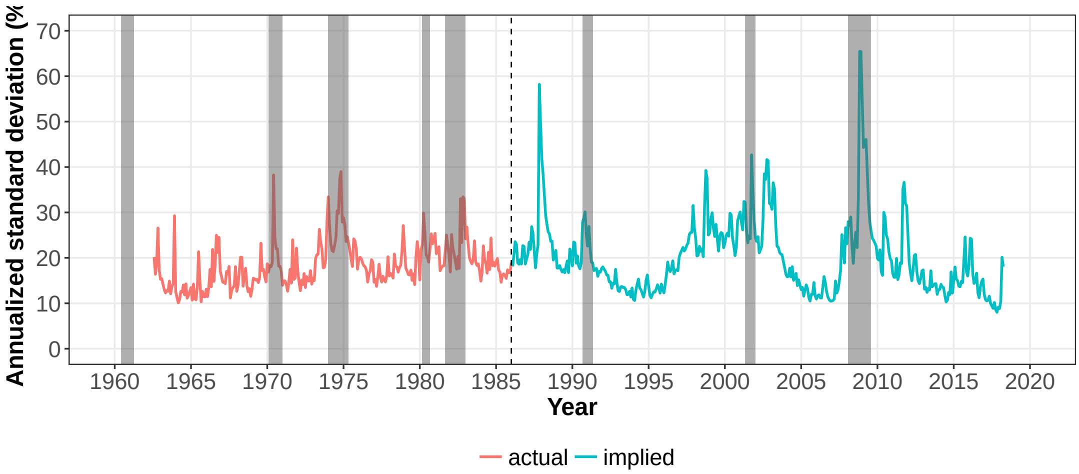

Figure 1.: Monthly U.S. stock market volatility including NBER recession dates (shaded). *Note:* From 1986 onwards the series shows the CBOE VXO index of percentage implied volatility, on a hypothetical at the money S&P100 option 30 days to expiration. Before 1986 actual monthly return volatilities are calculated as the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 - 2003.

2.1.2. A Survey-Based Measure: Michigan Survey of Consumers

The Michigan Survey was founded in 1946 and then conducted quarterly by means of interviews of minimum 500 households throughout the US from 1952 - 1977. Beginning with January 1978 the survey switched to a monthly frequency which is the year that Leduc and Liu (2016) start looking at the survey's data off of which they construct their uncertainty measure. Overall, the survey contains approximately 50 core questions that target various aspects of consumer sentiment and expectations which cover the three broad areas of personal finance, business conditions and buying conditions. Because of its forward-looking nature, the Michigan Survey is regarded as a helpful indicator of the future business cycle.[10]

[8] In the following we refer to this spliced version as the VXO index. Further, note that in the original contribution of Bloom (2009) the data logically only ranges until 2009 while we now have almost 10 more years of VXO data at our disposal.

[9] For the case of Australia, e.g. Moore (2016) exploits a slightly modified procedure by using the monthly average of the *absolute value* of daily changes arguing that it has a minimally higher correlation with the Australian counterpart of the U.S.-based VXO (option-implied volatility in the Australian ASX 200 index) and that it mitigates the effect of 'Black Monday' in 1987.

[10] For a more detailed survey description see https://data.sca.isr.umich.edu/fetchdoc.php?docid=24774.

Indices that are derived from survey questions are the 'Index of Consumer Expectations' (ICE),[11] the 'Index of Consumer Sentiment' (ICS) and the 'Index of Current Economic Conditions' (ICC).

For their uncertainty measure, Leduc and Liu (2016) look at the answers to the question *Speaking now of the automobile market - do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van or sport utility vehicle?'* which, for persons that answer anything other than 'Don't know' to that question, is followed by *Why do you say so?*. The percentage of respondents that report an "uncertain future" as the reason for why they consider it to be a bad time to buy a car or other durable goods serve's as Leduc and Liu (2016)'s uncertainty benchmark which we have plotted in Figure 2.

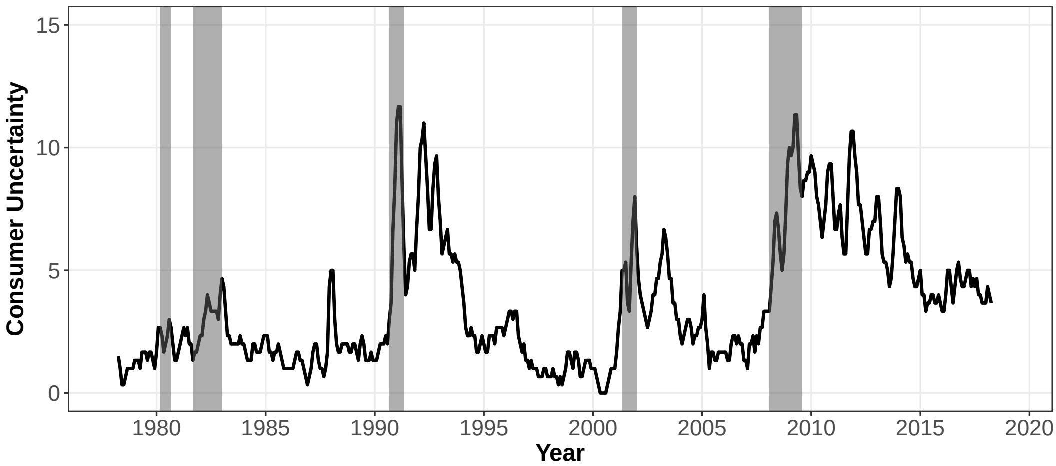

Figure 2.: Thomson Reuters/University of Michigan Survey of Consumers, Consumer Uncertainty. Shaded areas denote NBER recession dates in the U.S. Three-month moving averages are plotted

[11]The 'Index of Consumer Expectations' is included in the Composite Index of Leading Indicators published by the U.S. Department of Commerce, Bureau of Economic Analysis and focuses on three areas: how consumers view prospects for their own financial situation, how they view prospects for the general economy over the near term, and their view of prospects for the economy over the long term. The survey data that feeds into the construction of the index, however, represents only a small part of the entire survey data. For more detailed information see the survey's dedicated homepage at `https://data.sca.isr.umich.edu/`. In particular, the 'Time Series Codebook' is available at `https://data.sca.isr.umich.edu/subset/codebook.php` and the data can, among others, be conveniently downloaded from `https://data.sca.isr.umich.edu/subset/subset.php`.

Note to self:

- Orlik and Veldkamp (2014) go on and write: "Another commonly cited measure of uncertainty is business or consumer confidence. The confidence survey asks respondents whether their outlook on future business or employment conditions is 'positive', negative or neutral.' These questions are about the direction of future changes and not about any variance or uncertainty. They may be correlated with uncertainty because uncertainty is counter-cyclical.

- Basu und Bundick (2017) und Ledu and Lui (2016) verwenden als Unsicherheitsmaße einmal nur den VIX und einmal die ratio aus dem Michigan Survey (das ganze ist einfach direkt von der homepage herunterladbar)

- Here I should also refer to Bachmann et al. (2013).

- We should make use of the uncertainty measure used in Bachmann et al. (2013) and also create a similar plot compared to their Figure 22. Although the data for the IFO index is only available as of 1980, we could still make use of this and, e.g., compare the volatility indicator that Bloom (2009) uses with the uncertainty indicator used by Bachmann et al. (2013). Interestingly, Bachmann et al. (2013) even write in their footnote 16: "We follow here Bloom's (209) timing convention for stock market volatility."

- another approach is mentioned in Bachmann et al. (2013) where they write on p. 27: 'We also run an analogous SVAR with the 30 year corporate bond spread as the uncertainty measure. It is clear that negative long-run innovations have significant impact on uncertainty."

2.1.3. A News-Based Measure: Baker et al. (2015)

While string searching (and hence also matching) algorithms have been around since the early days of computer science, the methods rose in sophistication in the past decades accompanying ever larger amounts of text. Increased computing power in combination with more efficient algorithms nowadays allows the processing of masses of text within a reasonable amount of time. In combination with dedicated digital archives of various sorts, a rapidly growing body of literature within economics has turned to text search methods, primarily using digital newspaper archives, to answer a variety of research questions.[12]

[12] Examples of such approaches include, among others, Alexopoulos and Cohen (2009), Gentzkow and Shapiro (2010), Hoberg and Phillips (2010), Boudoukh et al. (2013), and Alexopoulos and Cohen (2015).

Making use of this newspaper-based technique and with a focus on *policy-related* economic uncertainty, Baker et al. (2015) build uncertainty indices trying to capture both the public's near-term and longer-term concerns as reflected in the newspaper coverage of certain key-terms[13]. The cornerstone of their work is the construction of a monthly and daily Economic Policy Uncertainty (EPU) Index for the U.S. and its evolution since 1985. This index reflects the frequency with which a specifically designed trio of terms is found in digital archives containing articles of ten leading U.S. newspapers:[14] "economic" or "economy" (E-terms set); "uncertain" or "uncertainty" (U-terms set); and one or more of the terms "Congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House" (P-terms set). This means that to be of relevance, an article must contain terms in all of the three categories.

To cater for the discrepancy of the overall volume of articles across newspapers and time yielded by the raw counts, Baker et al. (2015) implement the following steps to arrive at a reasonable index: (i) scaling of the raw counts by the total number of articles in the same newspaper and month, (ii) standardization of each monthly newspaper-level series to unit standard deviation from 1985 to 2009, (iii) averaging across the 10 papers by month, (iv) normalization of the 10-paper series to a mean of 100 from 1985 to 2009.

As shown in Figure 3, this results in a time series that, among others, spikes near tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the failure of Lehman Brothers, the 2011 debt ceiling dispute, and other major battles over fiscal policy (Baker et al., 2015). As an example of a period where the EPU index does not show any outlier, Baker et al. (2015) refer to the partial federal government shutdowns from November 1995 to January 1996.[15]

[13]In earlier drafts of their contribution, index components included the present value of future scheduled tax code expirations and disagreement among professional forecasters over future government purchases and consumer prices. To be able to extend their EPU measures over time and across countries, Baker et al. (2015) decided to focus on the newspaper approach but continue to report the other components on their dedicated website at http://www.policyuncertainty.com.

[14]The newspapers filtered by the search-algorithm are *USA Today*, *Miami Herald*, *Chicago Tribune*, *Washington Post*, *Los Angeles Times*, *Boston Globe*, *San Francisco Chronicle*, *Dallas Morning News*, *New York Times* and *Wal Street Journal*.

[15]Although these shutdowns did receive a considerable amount of press coverage, the share of articles mentioning the established trio of terms is extremely low.

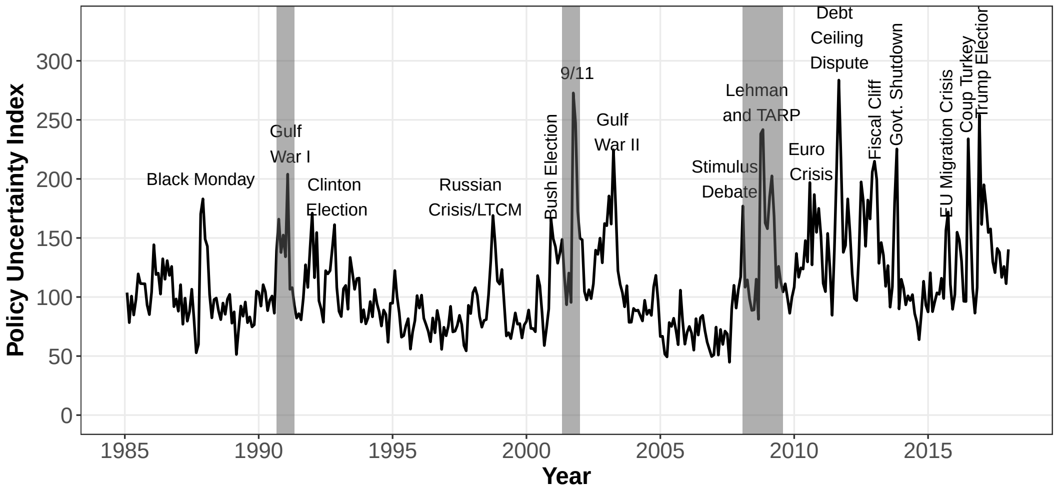

Figure 3.: EPU Index for the U.S., 01/1985 - 04/2018. *Note:* Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy, and one or more policy relevant terms: 'regulation', 'federal reserve', 'deficit', 'congress', 'legislation', or 'white house'. The series is normalized to mean 100 from 1985-2009 and based on queries run for the USA Today, Miami Herald, Chicago Tribune, Washington Post, LA Times, Boston Glove, SF Chronicle, Dallas Morning News, NW Times, and the Wall Street Journal. Shaded areas denote NBER recession dates in the U.S.
Original Figure in Baker et al. (2015) ranges until 2015. We have taken all available values until April 2018, inclusive.

Besides this index, Baker et al. (2015) extend their approach back in time, across countries (by constructing indices for 11 other countries including all G10 economies), and to specific (policy) categories.

For their historical EPU Index dating back to 1900, Baker et al. (2015) rely on the archives of six major U.S. newspapers[16] that have been published throughout the 20th century with slight modifications: to account for word usage patterns in newspapers, the E term set is expanded to include "business", "industry", "commerce" and "commercial" while the P term set is expanded by the words "tariff" and "war".[17] As shown in Figure 4, looking at the index from 1900 onwards, for Baker et al. (2015, p. 1594) the series "[...] highlights pre-World WAR II political developments and shocks like the Gold Standard Act of 1900, the outbreak of World War I, the Versailles conference in 1919, and a sustained surge in policy uncertainty from late 1931 when President Herbert Hoover, and then President Franklin Roosevelt, introduced a rash of major new policies. [...]"

[16]They are *Wall Street Journal*, *New York Times*, *Los Angeles Times*, *Boston Globe*, *Chicago Tribune* and *Washington Post*.

[17]Baker et al. (2015) report that for the overlapping period as of 1985 both the original term sets and the expanded ones show similar results while the expanded term set performs better for the first decades of the 20th century.

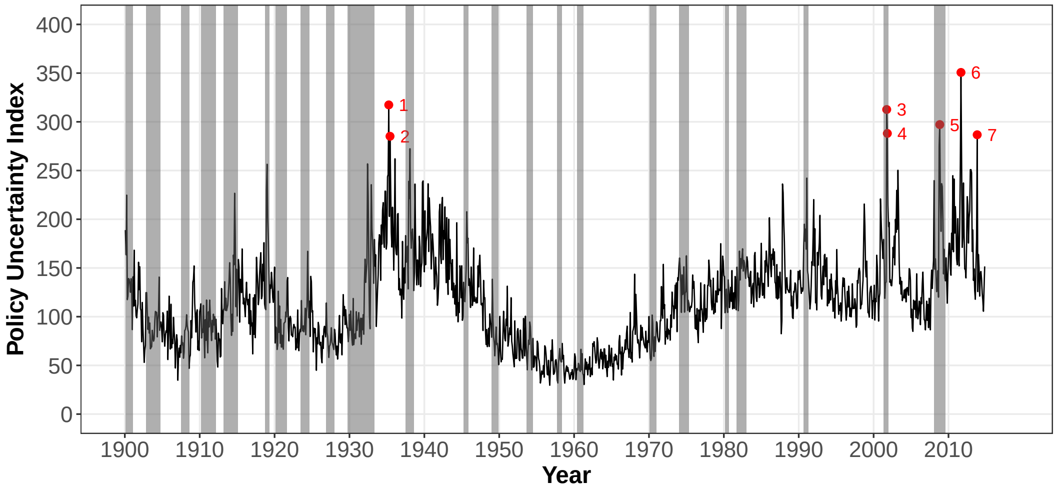

Figure 4.: EPU Index for the U.S. , 01/1900 - 10/2014. *Note:* Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy, and one or more policy relevant terms: 'regulation', 'federal reserve', 'deficit', 'congress', 'legislation', or 'white house'. The series is normalized to mean 100 from 1985-2009 and based on queries run for the USA Today, Miami Herald, Chicago Tribune, Washington Post, LA Times, Boston Glove, SF Chronicle, Dallas Morning News, NY Times, and the Wall Street Journal. Shaded areas denote NBER recession dates in the U.S.

Interestingly, the index also shows a slight upward drift since the 1960s which Baker et al. (2014) attribute either to the growth in government spending, taxes, and regulation or increased political polarization and its implications for the policy-making process. Corresponding to Figure 4, Table 1 showing the dates marked with red dots reveals that in the past two decades five times uncertainty rose to levels comparable to the Great Depression of the 1930s.

Table 1.: 7 Largest Spikes of U.S. EPU Historical

ID	Year	Month	EPU Historical Index
1	1935	3	317
2	1935	5	285
3	2001	9	313
4	2001	10	288
5	2008	10	297
6	2011	8	351
7	2013	10	287

The category-specific policy uncertainty indices are developed for the U.S. only by specifying more restrictive criteria for those articles that contain certain search terms.[18,19]

Table 5 reports all category-specific EPU indices together with an overall economic uncertainty (EU) index (dropping the third of the trio of necessary terms in the index constructions) and the EPU. –> Refer to Baker et al. (2015, p. 1602) to add some details about the peculiarities of the categorical breakdown of EPU!

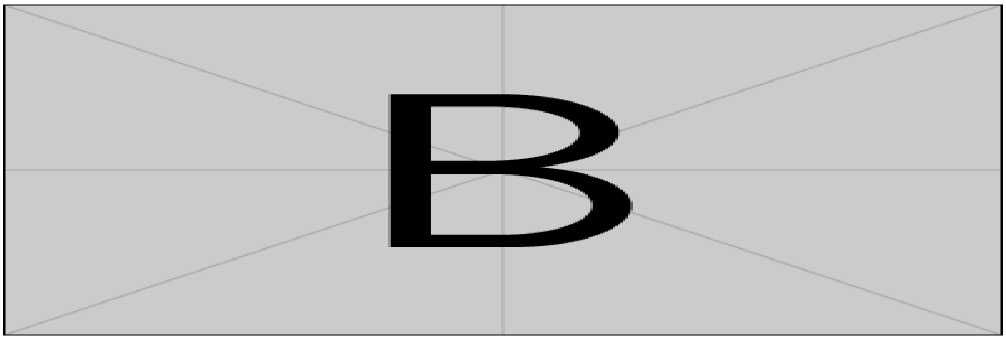

Figure 5.: Placeholder for 'Economic Policy Uncertainty by Policy Category and Time Period, 1985 - 2014. *Note:* The second row reports average values of the Newsbank Index of Economic Policy Uncertainty in each indicated period (scaling by the total number of articles in a period), expressed as a percentage of the average index value for the entire sample period from 1985:1 to 2014:12. For example, the value of 109 for Economic Policy Uncertainty from 1985:1 to 1990:6 says that the value of the index in that period is 109% of its average value over the full sample period. The top row reports the value of the Newsbank Index of Overall Economic Uncertainty, also expressed as a percentage of the average value of the news-based policy uncertainty index. Entries in Rows 1 to 12 index report analogous values for narrower policy categories based on news article references to specific policy-related terms. For example, the value of 26.8 for "Monetary Policy" from 2010:1 to 2013:10 says that the number of scaled references to monetary policy uncertainty in this period is 26.8 percent of the average number of scaled references to ALL forms of policy-related uncertainty during the 1985:1 to 2012:10 sample period. The categories in Rows 1 through 12 are not mutually exclusive in two respects. First, a given news article may discuss multiple distinct sources of uncertainty such as monetary policy and entitlement reforms. Second, some of the category boundaries overlap. For example, Medicaid is an entitlement program and a major part of the U.S. health care system. *Source: http://www.policyuncertainty.com*

To alleviate any potential concerns about the reliability, accuracy or consistency of their newspaper-based approach, Baker et al. (2015, p. 1595) counter with five observations that, in their view, reinforces their indices' ultimate purpose to proxy for movements in policy-related economic uncertainty: (1) there is a strong positive relationship between their EPU measure and implied stock market volatility (as another commonly used uncertainty-proxy)[20], (2) they

[18] E.g., the construction of a health care policy- or national security policy uncertainty index is based on the presence of additional terms like "health care", "hospital" or"health insurance" and "war", "terrorism" or "department of defense", respectively.

[19] Together, the collection of all indices is available at http://www.policyuncertainty.com, a dedicated homepage by the authors to make regular updates to their indices available.

[20] We report our correlation-measures in Table 3.

report a strong positive relationship between the newspaper-based EPU index and e.g., indices based on the frequency with which the Federal Reserve System's Beige Books mention policy uncertainty, (3) there seems to be no political slant since EPU indices based on right- or left-wing newspapers show not serious distortions, (4) an extensive audit study that included the manual reading of 12,000 randomly selected articles drawn from major U.S. newspapers which revealed a high correlation between this human- and the classical computer-generated index confirming the chosen set of terms used for the automated text search and lastly, (5) the market adoption of their indices by commercial data providers including Bloomberg, FRED, Haver, and Reuters to alleviate the demands from industry leads Baker et al. (2015) to conclude that the indices contain useful information for decision makers.

Note to self:

- BBD-index following Baker et al. (2015)
  The IMF Working Paper (Measuring Global and Country-Specific Uncertainty) is a very helpful resource because: (1) They compare various uncertainty measures and also give a hint of from where to retrieve news-based uncertainty-measures!
- Baker et al. (2015, p. 1593) write: "At the macro level, innovations in policy uncertainty foreshadow declines in investment, output, and employment in the United States and, in a panel vector autoregressive setting, for 12 major economies."
- Baker et al. (2015, p. 1596) write: "Our second approach fits vector autoregressive (VAR) models to U.S. data [...]. The U.S. VAR results indicate that a policy uncertainty innovation equivalent to the actual EPU increase from 2005-2006 to 2001-2012 foreshadows declines of about 6% in gross investment, 1.1% in industrial production, and 0.35% in employment.

2.1.4. A Forecast-Based Measure: Jurado et al. (2015)

Especially in contrast to stock market volatility and/or cross-sectional dispersion measures frequently deployed in uncertainty studies, Jurado et al. (2015) have designed a computationally and data-intensive approach by making use of a rich set of time series, computing the conditional volatility of the unforecastable component of the future value of each of these series and finally aggregating these conditional volatilities into one composite index.[21]

[21]Note that, apart from practical issues, Jurado et al. (2015, p. 1191) themselves explain the reliance on (most likely revised) "historical" data (instead of "real time" data) with their

To set their approach apart from other commonly used uncertainty measures, Jurado et al. (2015, p. 1178) argue that "[...] what matters for economic decision making is not whether particular economic indicators have become more or less variable or disperse *per se*, but rather whether the economy has become more or less *predictable*; that is, less ore more uncertain."

To formalize the rationale behind their approach, they define the h-period ahead uncertainty in the variable $y_{jt} \in Y_t = (y_{1t}, \ldots, y_{N_y t})'$, denoted by $U^t_{jt}(h)$, as the conditional volatility of the purely unforecastable component of the future value of the series, i.e.,

$$U^t_{jt}(h) \equiv \sqrt{\mathbb{E}\Big[(y_{jt+h} - \mathbb{E}[y_{jt+h}|I_t])^2|I_t\Big]}, \tag{2.1}$$

where the expectation $\mathbb{E}(\cdot|I_t)$ is taken with respect to information I_t available to economic agents at time t. Hence, if the expectation today (conditional on all available information) of the squared error in forecasting y_{jt+h} rises, uncertainty in the variable increases. The individual uncertainties at each date are then aggregated into a *macroeconomic uncertainty* index by using aggregation weights w_j as follows:

$$U^t_{jt}(h) \equiv plim_{N_y \to \infty} \sum_{j=1}^{N_y} w_j U^y_{jt}(h) \equiv \mathbb{E}_w\Big[U^y_{jt}(h)\Big] \tag{2.2}$$

Based on the above definitions, Jurado et al. (2015) emphasize two features that are central to their approach:

1. they distinguish between *uncertainty* in a series y_{jt} and its *conditional volatility* and argue that the proper measurement of uncertainty requires the removal of the entire forecastable component $\mathbb{E}[y_{jt+h}|I_t]$ before the computation of the conditional volatility; without accounting for this, the argument goes, forecastable variation is erroneously classified as "uncertainty". According to Jurado et al. (2015), this is taken into account

goal of forming the "[...] most historically accurate estimates of uncertainty at any given point in time in [their] sample".

only in very few occasions in the literature.

2. they claim that macroeconomic uncertainty is "a measure of the common variation in uncertainty across many series" and not equal to the uncertainty in any single series y_{jt}; Jurado et al. (2015) see this as an important argument because of uncertainty-based theories of the business cycle that typically require the existence of common (often countercyclical) variation in uncertainty across large numbers of series; Jurado et al. (2015) hence put their econometric estimation of uncertainty insofar to test, as they expect to find evidence of such an aggregate uncertainty factor common to many series, if the above assumption turns out to be correct.

Jurado et al. (2015)'s econometric approach then consists of three parts:

i estimation of the forecastable component $\mathbb{E}[y_{jt+h}|I_t]$: this is achieved by, first, running a factor analysis on a large set of predictors (132 macro time series) $\{X_{it}\}, i = 1, 2, \ldots, N$ whose linear span/hull comes as close as possible to I_t; second, making use of the formed factors, $\mathbb{E}[y_{jt+h}|I_t]$ is then approximated by means of a diffusion index forecasting model ideal for data-rich environments (the diffusion indices can then be treated as known in the subsequent steps)

ii with the definition of the h-step-ahead forecast error as $V^y_{jt+h} \equiv y_{jt+h} - \mathbb{E}[y_{jt+h}|I_t]$, Jurado et al. (2015) estimate the conditional volatility of this forecast error, i.e., $\mathbb{E}[(V^y_{t+h})^2|I_t]$ at time t by specifying a parametric stochastic volatility model for both the one-step-ahead prediction errors in y_{jt} and the analogous forecast errors for the factors (from step i above);
these volatility estimates are then used to recursively compute the values of $\mathbb{E}[(V^y_{t+h}|I_t]$ for $h > 1$.

iii in the last step, the *macroeconomic uncertainty* index $U^y_t(h)$ is constructed from the individual uncertainty measures $U^y_{jt}(h)$ where the base-case is the equally-weighted average of individual uncertainties

While Jurado et al. (2015) apply their approach to two large dataset with economic time-series (one monthly dataset containing hundreds of macroeconomic and financial indicators and one quarterly dataset containing 155 firm-level observations on profit growth normalized by sales), here we only confine ourselves to the former, i.e., their *common macro uncertainty* index.

Their resulting estimated measures of time-varying uncertainty are plotted in Figure 6 and reveals 'only' three big episodes of uncertainty: the months during the recessions from 1973-1974 and 1981-1982 and the months during the Great Recession of 2007-2009 (being the most striking episode of heightened uncertainty, followed by the 1981-1982 recession as a close second).[22,23]

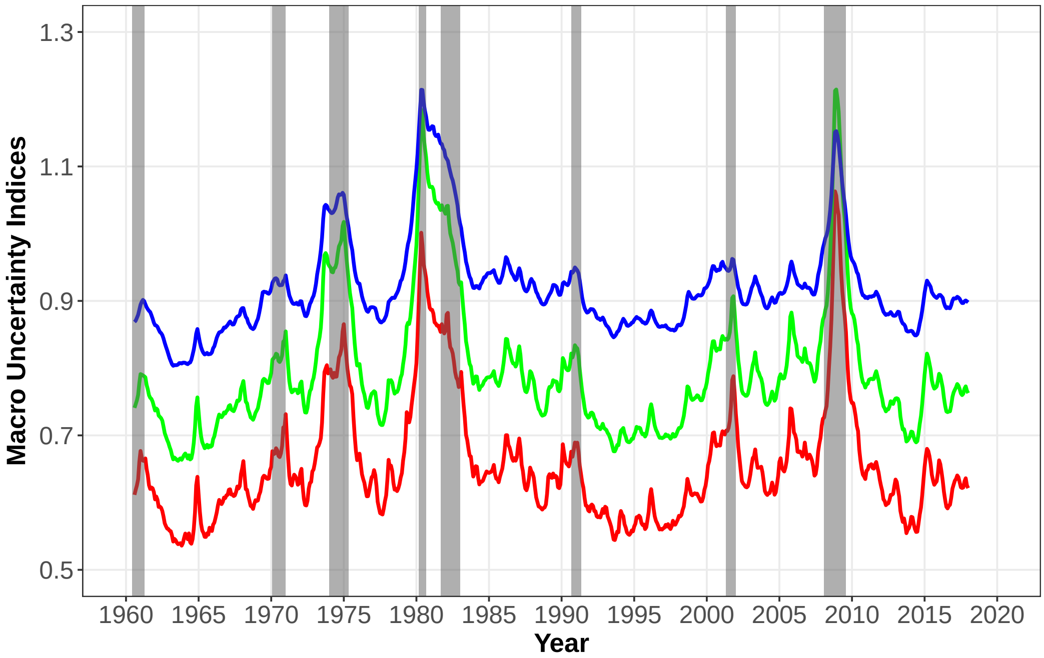

Figure 6.: Aggregate Uncertainty: $h = 1, 3, 12$. *Note:* Horizontal lines indicate 1.65 standard deviations above the mean of each series. Data are monthly and span the period 1960:7-2017:12. Red shaded areas correspond to dates where volatility series exceeds 1.65 standard deviation above the mean of the h1-series. Grey shaded areas denote NBER recession dates in the US.
Original Figure 1 in Jurado et al. (2015) spans until 2011. We have taken all available values until December 2017, inclusive.

The IMF Working Paper (Measuring Global and Country-Specific Uncertainty) is a very helpful resource because: (4) They also succinctly describe the

[22]See Table 2 below for the exact dates including the maximum value for the index for each identified episode of high uncertainty.

[23]Jurado et al. (2015) report that a closer look at the estimates reveals that the three series with the highest uncertainty are a producer price index for intermediate materials, a commodity spot price index, and employment in mining between 1973:11 and 1975:3, the Fed funds rate, employment in mining, and the three months commercial paper rate for the 1980:1 and 1982:11 episode and the monetary base, non-borrowed reserves and total reserves between 2007:12 and 2009:6. Jurado et al. (2015) conclude these results to be consistent with the historical account.

Table 2.: Periods of high uncertainty according to macro uncertainty index h=1.

Start	End	Duration	Maximum Year/Month	Maximum Value
Sep 1974	Mar 1975	7 months	Jan 1975	0.87
Jan 1980	Aug 1982	31 months	May 1980	1.00
Jul 2008	Sep 2009	15 months	Nov 2008	1.06

uncertainty-measure developed by Jurado et al (which is very complicated!)

2.1.5. Additional Parts for Later Usage

Orlik and Veldkamp (2014) discuss data used to proxy for uncertainty in Section 5 and offer a useful taxonomy which we could make use of as well! They write: "Our model generates a measure of economic uncertainty. In this section, we describe the commonly used proxies of uncertainty, analyze their theoretical relationship with conditional variance and then compare their statical properties to those of our measure. Orlik and Veldkamp (2014) mention the following uncertainty measures:

Another interesting sentence that is written in Bachmann et al. (2013), p. 10: "Measuring the subjective uncertainty of decision makers is inherently difficult. Ideally, one would like to elicit a subjective probability distribution over future events from the managers, as has been done in Guiso and Parigi (1999) for Italian firms. with this probability distribution it is straightforward to compute a measure of subjective uncertainty for firms' decision makers. However, to the best of our knowledge such probability distributions are not available repeatedly and over long time horizons. Therefore, reserachers have to rely on proxies."

Note to self:

- I could potentially at some point refer to economic sentiment indicators like https://www.oenb.at/en/Statistics/Standardized-Tables/Economic-and-Indust Economic-Indicators/Economic-Sentiment-Indicator-for-the-Euro-Area.html or https://data.europa.eu/euodp/data/dataset/c04BuUz6WXIQGJkHPwLug

2.1.6. Critique of the Various Measures

- Comparing the VXO to their own macro uncertainty index, Jurado et al. (2015, p. 1201) write that "[...] it is difficult to imagine that the level of macro uncertainty in the economy in October 1987 (not even a recession year) was on par with the recent financial crisis."
- Orlik and Veldkamp (2014) go on and write: "Other proxy variables for uncertainty are informative, but have a less clear connection to a conditional variance definition of uncertainty.' (then they go on and write about business or consumer confidence, market volatility index (VIX), etc.)'
- mentioned in Jurado et al. (2015, p. 1182): "[...] we emphasize here that the measures of dispersion and stock market volatility studied may or may not be tightly linked to true economic uncertainty. Indeed, one of the most popular proxies for uncertainty is closely related to financial market volatility as measured by the VIX, which has a large component that appears driven by factors associated with time-varying risk-aversion rather than economic uncertainty (see Bekaert et al. (2013))
- Moore (2016, p. 4) writes: "The drawback of these stock volatility measures is that they are only indirectly connected to economic activity. Although company earnings are connected to economic activity, much of the short-run variation in stock prices is driven by other factors (Shiller 1981; Cochran e2011). Although these factors may related to economic uncertainty, the connection to economic activity is not clear. These measures are also asymmetric - increases in the measures accompany large falls in stock prices; large gains in stock prices are less common.
- IMF Working Paper, Measuring Global and Country-Specific Uncertainty, p.1: "A ubiquitous proxy is the implied or relaized volatility in stock

markets, such as VIX, e.g. Bloom (2009). However, the volatility in Wall Street might not reflect uncertainty in Main Street. For instance, changes in the VIX might be due to leverage or financiel stress, despite low levels of economic uncertainty; For instance, changes in the VIX might be due to leverage or financial stress, despite low levels of economic uncertainty; see Bekaert et al. (2013).

- IMF Working Paper, Measuring Global and Country-Specific Uncertainty, p.1: "Jurado et al. (2015) develop an alternative measure of economic uncertainty: the common variation in uncertainty across hundreds of economic series. Their measure reflects uncertainty around objective statistical forecasts, rather than perceived uncertainty by market participants. Moreover, as they focus on common, not idiosyncratic, unceratinty, there is no role for private information and heterogeneous agent models.

- IMF Working Paper, Measuring Global and Country-Specific Uncertainty, p.1: "But, like all measurements of this type, this news-based uncertainty measure puts a high bar for the attentiveness of reporters and editors, who might miss uncertainty events if they neglect to write a story on the subject."

- IMF Working Paper, Measuring Global and Country-Specific Uncertainty, p.4: Regarding cross-sectional dispersion measures: When disagreement is taken to indicate uncertainty, the underlying assumption is that this inter-personal dispersion measure is an acceptable proxy for the average dispersion of intra-personal uncertainty. As shown by Lahiri and Sheng (2010), however, disagreement is only a part of uncertainty and misses an important component: the volatility of aggregate shocks.

- similarly, Bontempi et al. (2016, p. 12) write: "The (i) VIX is used in many empirical studies (most prominently in Bloom (2009)). But one caveat that emerges from the use of the VIX to proxy uncertainty concerns its ability to represent macroeconomic uncertainty, since it is based on stock market information alone. According to Bekaert et al. (2013), the VIX does not only reflect uncertainty but can be broken down into uncertainty and risk-aversion. Since risk aversion accounts for a sizeable part of the VIX,[24], even more caution should be taken when considering it as a proxy of macro-economic uncertainty.

- in their non-technical summary, Bekaert et al. (2013) write: "Second, Bloom (2009) and Bloom, Floetotto and Jaimovich (2009) show that heightened "economic uncertainty" decreases employment and output. It is therefore conceivable that the monetary authority responds to uncertainty shocks, in order to affect economic outcomes. However, the VIX index, used by Bloom (2009) to measure uncertainty, can be decomposed into a component that reflects actual expected stock market volatility (uncertainty) and a residual, the so-called variance premium, that reflects risk aversion and other non-linear pricing effects, perhaps even Knightian uncertainty. Establishing which component drives the strong co-movements between the monetary policy stance and the VIX is therefore particularly important"

- related to our empirical analysis: Jurado et al. (2015, p. 1184) write: "An important unresolved issue for empirical analysis of uncertainty concerns the persistence of uncertainty shocks. [...] Researchers (e.g., Schaal 2011) have argued that empirical proxies for uncertainty, such as the cross-sectional dispersion in firms' sales growth, are not persistent enough to explain the prolonged levels of unemployment that have occurred during and after some recessions, notably the 2007-2009 reession and its aftermath. Here we provide new measures of uncertainty and its persistence, finding that they are considerably more persistent than popular proxies such as stock market volatility and measures of dispersion.

- With regard to cross-sectional dispersion measures in N_A analysts' or forms' subjective expectations as a measure of uncertainty, Jurado et al. (2015, p. 1182) also have a very strong opinion: "A separate strand of the literature focuses on cross-sectional dispersion in N_A analysts' or firms' subjective expectations as a measure of uncertainty:

$$D^A_{jt}(h) = \sqrt{\sum_{k=1}^{N_{A_t}} w^A_k \Big(y_{jt+h} - \mathbb{E}(y_{jt+h}|I_{A_k,t}) \Big)^2}, \tag{2.3}$$

[24]For this reason, the VIX is usually referred to as the "fear index" (see, e.g., ?).

where $I_{A_k,t}$ is the information of agent k at time t, and w_k^A is the weight applied to agent k. One potential advantage of using $D_{jt}^A(h)$ as a proxy for uncertainty is that is treats the conditional forecast of y_{jt+h} as an observable variable, and therefore does not require an estimation of $\mathbb{E}(y_{jt+h}|I_{A_k,t})$. Bachmann et al. (2013) follow this approach using a survey of German firms and argue that uncertainty appears to be more an outcome of recessions than a cause, contrary to the predictions of theoretical models such as Bloom (2009) and others. [...] While analysts' forecasts are interesting in their own right, there are several known drawbacks in using them to measure uncertainty. First, subjective expectations are only available for a limited number of series. For example, of the 132 monthly macroeconomic series we will consider in this paper, not even one-fifth have corresponding expectations series. Second, it si not clear that the responses elicited from these surveys accurately capture the conditional expectations of the economy as a whole. The respondents typically sampled are practitioner forecasters; some analysts' forecasts are known to display systematic biases and omit relevant forecasting information (So, 2013), and analysts may have pecuniary incentives to bias their forecasts in a way that economic agents would not. Third, disagreement in survey forecasts could be more reflective of differences in opinion than of uncertainty. Fourth, Lahiri and Shen (2010) show that, even if forecasters are unbiased, disagreement in analysts' point forecasts does not equal (average across analysts) forecast error uncertainty unless the variance of accumulated aggregate shocks over the forecast horizon is zero. Bachmann et al. (2013) acknowledge these problems and are careful to address them by using additional proxies for uncertainty, such as an ex post measure of forecast error variance based on the survey expectations.

- Further, Jurado et al. (2015) (pp. 1178) argue, that "unfortunately, the conditions under which common proxies are likely to be tightly linked to the typical theoretical notion of uncertainty may be quite special. For example, stock market volatility can change over time even if there is no change in uncertainty about economic fundamentals, if leverage changes, or if movements in risk aversion or sentiment are important drivers of

asset market fluctuations.
Cross-sectional dispersion in individual stock returns can fluctuate without any change in uncertainty if there is heterogeneity in the loadings on common risk factors. similarly, cross-sectional dispersion in firm-level profits, sales, and productivity can fluctuate over the business cycle merely because there is heterogeneity in the cyclicality of firms' business activity."

- Bontempi et al. (2016, p. 13) write: "Although independent of any single observable economic indicator or event, the macroeconomic uncertainty measure following Jurado et al. (2015) is a computationally intensive black box that is not directly linked to the uncertainty perceived by the general public.

2.2. Properties of Selected Measures and Stylized Facts

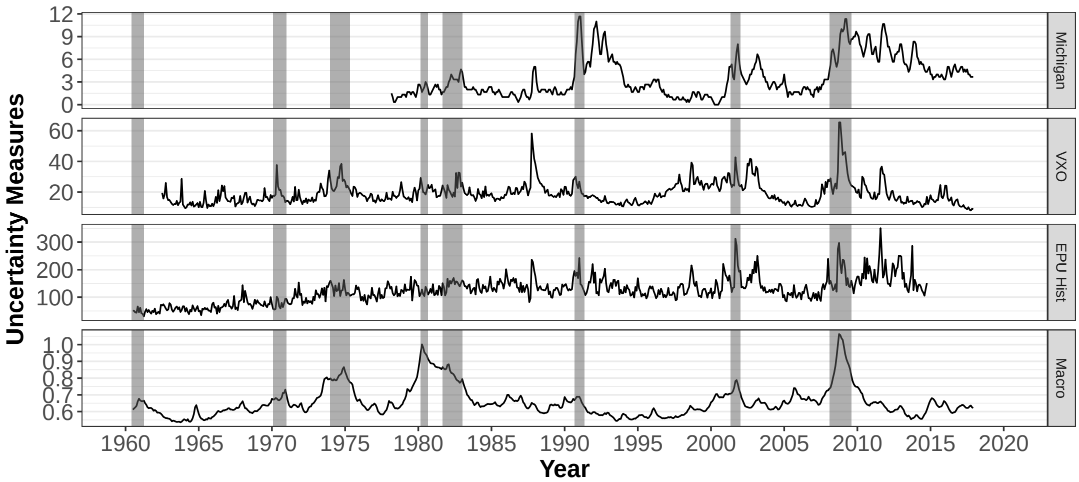

Figure 7.: Comparison of uncertainty measures (facetted). *Note:* Shaded areas denote NBER recession dates. Data frequencies are monthly. The macro uncertainty series starts in July 1960, the EPU in January 1960, the consumer uncertainty series (Michigan Survey) in March 1978 and the VXO in July 1962.

Figures 7 (on different scales) and 13 (normalized to the same scale) show all uncertainty measures we have considered so far including NBER recessions for the U.S.

A first preliminary visual comparison highlights that similar to Bachmann et al. (2013)'s assessment in their own comparison, almost all recession periods correspond to elevated uncertainty across all measures. Apart from this commonality, the VXO and EPU are affected by much noisier fluctuations over time than e.g., the macro uncertainty index. The VXO and EPU often move together prior to the crisis with distinct variations due to pronounced reactions of the VXO series to events with a connection to financial markets (e.g., the Asian financial crisis, the WorldCOM fraud, the Lehman Brothers failure, etc.). On the other hand, the EPU shows stronger spikes related to e.g., the Gulf Wars, presidential elections, and fiscal uncertainties due to tax or spending debates which causes the EPU to be elevated during most of the recovery period showing more variation including several spikes. This suggests that the EPU, by construction, indeed reacts much stronger to the political turmoil in the past decade than financial markets themselves.[25]

Description of difference between VIX and MSoC: "However, the two series appear otherwise very different. One notable difference is in 1997-1998. The VIX surged following the East Asian financial crisis and the Russian debt crisis, but consumer uncertainty remained at historically low levels. Another notable difference is in late 2010, when the U.S. economy faced the possibility of fiscal cliff" that could potentially trigger large tax increases and government spending cuts if Congress and the White House failed to reach an agreement about deficit reductions. In that period, consumer uncertainty remained elevated but the VIX was very low. Anecdotal evidence aside, the two measures of uncertainty are only weakly correlated, with a sample correlation of about 0.24 during the period from January 1986 - October 2013. The macro uncertainty index overall stands out with an overall smoother trajectory and marked spikes that correspond to recessions but also, as aptly formulated by Jurado et al. (2015) themselves, significant independent variation as compared to the other commonly used uncertainty measures suggesting that "[...] quantitatively important uncertainty episodes occur far more *in*frequently[26] than what is indicated from common uncertainty proxies, but that when they *do* occur, they display larger and more persistent correlations with real activity" (Jurado et al., 2015, p. 1181). This observation can be confirmed by looking

[25]Specifically being aware of these differences between the VXO and their EPU measure, Baker et al. (2015) construct a variation of their original EPU to be more strongly geared towards uncertainty on equity markets. Naturally, they report this financed-based EPU to correlate more strongly with the VXO/volatility series. For Baker et al. (2015) this exercise serves as a proof-of-concept in so far that a reasonable proxy for a specific *type* of economic uncertainty can indeed be constructed using text-search techniques and that the variations between the VXO/volatility series and the original EPU are important and justified by construction.

[26]Italics added.

Table 3.: Correlation matrix of uncertainty measures. [check correlation between EPU and Macro! Baker et al. (2015)] report a value of 0.42 while we get 0.15!

	MSoC	VXO	EPU	Macro
MSoC	1	0.510	0.600	0.340
VXO	0.510	1	0.530	0.630
EPU	0.600	0.530	1	0.150
Macro	0.340	0.630	0.150	1

at Figures 7 and 13[27] where increases in the macro uncertainty estimates are mostly associated with protracted recessions whereas more modest recessions are accompanied with smaller spikes. A period where the macro uncertainty index stands out is the recessionary period from 1980-1982: throughout this episode the index is highly elevated while other measures are comparatively low. The VXO on the other hand also shows spikes outside of recession periods that correspond to events exclusively related to stock-markets. For example, the large spike commonly to as 'Black Monday' (October, 19th 1987) when stock markets experienced their largest single-day percentage decline ever recorded, is only visible in the MSoC (with a timely delay - almost not visible) and the EPU. The macro uncertainty index, however, barely moves around that time. Interestingly, the EPU shows the largest spike surrounding the years 2001-2001 (the dot-com bubble).

Despite an overall co-movement between the series, the identified episodes of substantial variation in the processes' dynamics suggest that "[t]hese [time series] are clearly not measures of the same [latent] stochastic process [...]" (Orlik and Veldkamp, 2014, p.).

To shed some light on the above statement, we will comparatively discuss a few univariate and multivariate properties of the various uncertainty measures in turn.

Table 4 reports several summary statistics including key figures regarding the *distribution* of the uncertainty measures, their *cyclicality* and its nexus to the business cycle, *persistence* and whether we have any evidence for non-

[27] And also Table 4 which we will discuss below.

stationarity. The results point at a few stylized facts:
First, none of the measures passes the Shapiro-Wilk test, meaning that their respective distributions are significantly different from the normal distribution. This is in line with the figures on skewness and kurtosis: the distribution of changes in the measures are positively skewed and show excess kurtosis (fat tails), most pronounced for VXO and EPU indicating that there are more extreme values in these series as compared to Macro1 and Macro12.[28]. Together, these observations point at tails on the right side of the distribution being longer than the ones on the left (meaning that the majority of the density's mass and the median lies to the left of the means). Similarly to the dynamics of business cycles, the above findings suggest that increases in the uncertainty measures tend to be larger than decreases. In other words, uncertainty increases faster than it decreases (Moore, 2016). Further, across all uncertainty measures, the VXO and EPU suggest a higher variability (according to the variation coefficients) which is also visible from the visual inspection of Figures 7 and 13.

Second, uncertainty appears to be countercyclical. The measures largely show means and variances that are higher during recessions versus expansions. This is further supported by negative contemporaneous correlations of the uncertainty measures with key economic indicators like industrial production and employment in manufacturing. The figures are strongest for the macro uncertainty series (Macro1 and Macro12) while VXO, Michigan and EPU are more weakly associated with the business cycle. In line with Bloom (2014), uncertainty seems to be higher during recessions.[29]

Third, as persistence seems to be a relevant ingredient of the impact of uncertainty on business cycles as shown by Schaal (2017), the estimated half-life shocks (derived from the AR(1)-coefficients) of Macro1 and Macro12 with 57 and 129 months, respectively, show a much higher persistency than the other uncertainty proxies with approx. 4 months which is "[...] a finding relevant for theories where uncertainty is a driving force of economic downturns, including those with more prolonged periods of below-trend economic growth" (Jurado

[28] The only exception being the kurtosis figure for Michigan with -0.66.

[29] The unconditional negative correlations are, of course, uninformative about causation between real activity and uncertainty.

[30] KPSS-test with $H_0 =$ (trend/level) stationary.

Table 4.: Summary Statistics on the Dynamics of Uncertainty Proxies.
Note: IP-corr(k) and EMP-corr(k) are the absolute cross-correlation coefficients between a measure of uncertainty and the 12 month moving average of industrial production or employment in manufacturing growth in period $t+k$, i.e., IP-corr(k) $= |corr(u_t, \Delta\%IP_{t+k}|$ and EMP-corr(k) $= |corr(u_t, \Delta\%EMP_{t+k}|$. A positive k means uncertainty is correlated with future IP/EMP. Half-lifes are based on estimates from a univariate AR(1) model for each series and calculated as $HL = ln(2)/ln(AR(1).coef)$. The sample for each uncertainty measure is the largest available, starting in July 1962 in the case of VXO, EPU, Macro1 and Macro12 and in March 1978 for Michigan.

	VXO	Michigan	EPU	Macro1	Macro12
Distribution					
Coeff. of Variation (σ/μ)	0.33	0.78	0.37	0.14	0.08
Skewness (Levels)	1.23	1.11	0.77	1.67	1.61
Excess Kurtosis (Levels)	−0.98	−2.37	−1.21	0.23	−0.08
Skewness (Change)	0.69	0.29	0.48	0.75	0.90
Excess Kurtosis (Change)	2.06	−0.66	3.33	0.35	0.60
Shapiro-Wilk (p-value)	0	0	0	0	0
Cyclicality					
Downturn/Upturn μ ratios	1.35	1.73	1.14	1.25	1.13
Downturn/Upturn σ ratios	0.98	1.3	1.33	1.72	1.58
IP-corr(0)	−0.36	−0.27	−0.33	−0.64	−0.61
IP-corr(-12)	−0.15	−0.36	−0.22	−0.37	−0.33
IP-corr(+12)	−0.13	0.13	−0.17	−0.21	−0.29
EMP-corr(0)	−0.43	−0.28	−0.33	−0.63	−0.57
EMP-corr(-12)	−0.21	−0.30	−0.24	−0.24	−0.20
EMP-corr(+12)	−0.24	0.18	−0.21	−0.34	−0.40
Persistence					
AR(1)	0.83	0.85	0.81	0.99	0.99
Half Life (in months)	3.66	4.22	3.26	57.8	129
Stationarity Tests					
Level Stationary (p-value)[30]	0.02	0.01	0.01	0.09	0.03
Trend Stationary (p-value)	0.10	0.05	0.01	0.01	0.01

et al., 2015, p. 1193).

Together, one could postulate that the dynamics of uncertainty tend to be characterized by "[...] large [upward] spikes [...] after major events, followed by slow reversion" (Moore, 2016, p. 14).

While Table 4 looked at all recessionary periods together, Figure **??** shows the evolution of uncertainty in the U.S., starting 9 months after uncertainty reached its peak during the respective recessions since 1960.[31]

While Table 4 already hints at the strong countercyclicality of uncertainty –> reproduce the Table from Kose and Terrones, 2012 where they differentiate various degrees of uncertainty and its effects on production, etc.

Note to self:

- IMF, Kose and Terrones, 2012, p. 1: –> Derived from this statement, I should reconstruct the regressions of Kose and Terrones to prove those two points: "Uncertainty is shown to have a harmful impact on economic activity. Second, as experienced acutely since the global financial crisis, uncertainty is highly COUNTERCYCLICAL. Thirds, cross-country evidence indicates that high uncertainty is OFTEN ASSOCIATED WITH DEPER RECESSIONS AND WEAKER RECOVERIES.

Note to self:

- here we should compare the statistical features at both the univariate (persistence, seasonality and variability over time) and multivariate (Granger causality and contemporaneous correlation) levels!! (compare to Bontempi et al. (2016))!!!! i.e., add time-series analysis of the uncertainty-measures! (like the one performed in Bontempi et al, 2015) to this section!

- The following sentence is taken from Bloom (2009) where Bloom explains the rationale for taking the stock-market volatility: Here I should mention what is written in Bloom (2009): 'The evidence presented in Table I shows that a number of cross-sectional measures of uncertainty are highly correlated with time series stock-market volatility. Stock-market volatility has also been previously used as a proxy for uncertainty at the firm level (e.g., Leahy and Whited (1996) and Bloom, Bond, and Van REenen (2007)).'

- Here I should replicate some of the stylized facts that Bloom has mentioned in his 2012 paper as well as in the corresponding Power-Point-Presentation!

  I have to read the review article from Nicholas Bloom where he starts the abstract with: "This review article tries to answer four questions: (i) what are the stylized facts about uncertainty over time; (ii) why does uncertainty vary; (iii) do fluctuations in uncertainty matter; and (iv) did higher uncertainty worsen the Great Recession?

- Bontempi et al. (2016, p. 3) write: "The three previous approaches al have their pros and cons. On the one hand, the pre-selection of directly obesrvable specific events is easy to perceive but somewhat arbitrary. On the other hand, the methodological approaches that extract uncertainty estimates from latent processes are statistically and economically sound but are also very complex black boxes not strictly related to observable indicators of uncertainty."

- the differences between the macro uncertainty index of Jurado et al. (2015) and other uncertainty

[31] We look at the 1982, 1983, 1991, 2002 and 2009 recessions and exclude the 1971, 1975 recessions because our measure from the Michigan Survey only starts in 1978.

measures cause Jurado et al. (2015, p. 1180) to conclude: "Taken together, the findings imply that most movements in common uncertainty proxies, such as stock market volatility (the most common), and measures of cross-sectional dispersion, are not associated with a broad-based movement in economic uncertainty as defined in (2). This is important because it suggests that much of the variation in common uncertainty proxies is not driven by uncertainty.

2.3. Identification of Shocks and Causality

We do look at measures that try to model the same underlying stochastic process but .....cat in a dark room etc. Because in the empirical analysis we will look at samples that start in 07/1962 at the earliest (apart from the Michigan Survey), as of now we will choose that date as our starting date (unless an uncertainty measure has data only later). The end-date refers to the original estimation window used by Bloom (2009).

Bloom manages to tell a story and blablabla

mention that we get slightly different results!

I should move the entire part about the identification of shocks to this dedicated section (and hence de-clutter the figures with the Bloom-shocks and the shocks identified for the Macro-time-series; In this section would be the spot to discuss shock-measures in greater detail!

Note to self: We argue that uncertainty is a local property and not a global property, meaning that some sort of learning effect takes place (das muss ich dann noch etwas näher ausführen!) in people and that an algorithm that takes local properties into account is to be preferred!

Wichtig: Bei Bloom's Herangehensweise haben wir das Endpunkt-Problem! (siehe Finanzkrise, die überhaupt nicht mit-einfließt)!

2.3.1. The Bloom-Shock

Note to self:

- I definitely have to take into account what Hans said: the construction of the Bloom-shock explicitly tries to argue that the shocks are exogenous by construction - here I should

Bloom (2009) introduces stock-market volatility indicators (periods of high uncertainty; henceforth called 'Bloom-shocks') with the following approach:

i detrending the uncertainty measure using a HP-filter with $\lambda = 129,600$;

ii shocks are then chosen as those events with stock-market volatility more than 1.65 standard deviations above the HP-detrended mean (selected as the 5% one-tailed significance level) of the measures' time series; thereby each month is being treated as an independent observation

iii within a series of resulting adjacent shock-months, Bloom (2009) further distinguishes between months corresponding to the maximum volatility and months corresponding to the first occurrence of significantly high volatility; the actual 'Bloom-shocks' are months with the maximum volatility

In Figure 8 we can see what the construction of 'Bloom-shocks' would mean for all uncertainty measures we have introduced in Section 2.1. Correspondingly, for a more detailed reference, Table A.3 outlines all 'shock' - periods in greater detail across all measures including information about 'first' (f) and 'maximum' volatility.

To be able to compare our results to Bloom (2009) in case of the VXO, for both the construction of Figure 8 and Table A.3 we have limited the data for the shock-calculation for all uncertainty measures to the period of 07/1962 - 06/2008[32].

In Table A.1, Bloom (2009, p. 676) reports 17 events of maximum stock market volatility and assigns each of theses event dates to actual events categorized as either 'war', 'terror', 'oil', or 'economic'. In our reproduction of Bloom's Table in Table A.3 we record a few discrepancies: we do not pick up November 1978 (OPEC II) and instead pick up October 1966, August 1982, January 1991, August 2007 and November 2007.

Apart from this, a comparison of the identified shock-periods across our uncertainty measures confirms our observation from Section 2.2: despite a consider-

[32] 02/1978 in the case of the Michigan Survey

able amount of overlapping shock-periods, the various uncertainty measures at the same time also produce distinct shock-periods that are limited to one or maximum two of the uncertainty measures simultaneously, suggesting that indeed the various measures seem to be steered partly by a common underlying stochastic process in combination with an own distinct component (financial in the case of the VXO, political in the case of the EPU, etc).

the most notably observations are

. While easily deductible from Table A.3, we have reproduced our He thereby links all identified shocks by actual events classified in 'Terror', 'War', 'Oil', and 'Economic'. But since the classification of a 'shock' is an in-sample property and changes depending on the time-span usw..... Mention: The result has to be seen with caution because it is an in-sample property: to highlight this we have produced the exact same plot for the full available samples of the various uncertainty measures that are avialable (including the financial crisis) this time –> This significantly alters the picture!!!

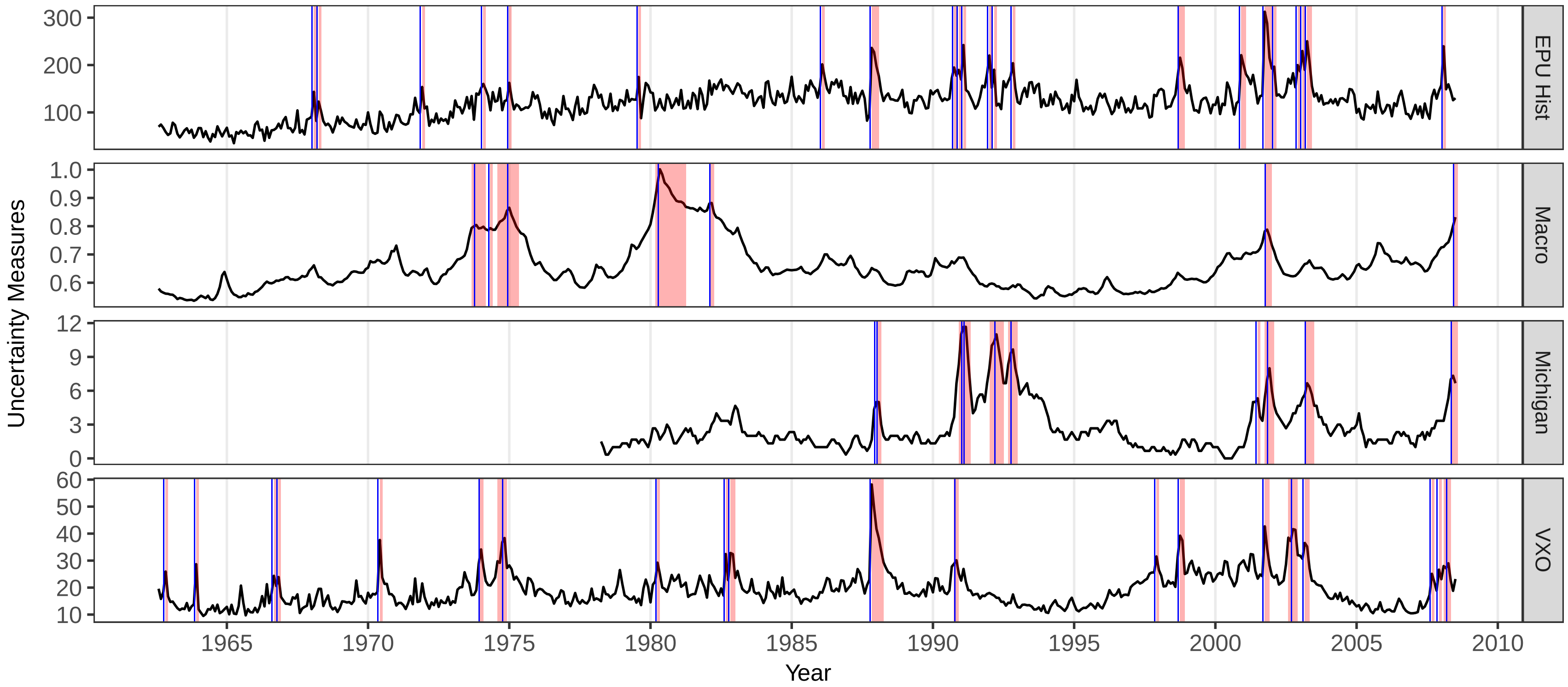

Figure 8.: Comparison of uncertainty measures including 'Bloom-shocks' (facetted). *Note:* Shaded areas denote shock-periods (high uncertainty periods) following Bloom (2009) according to the following definition: high uncertainty periods are defined as periods where a series value is more than 1.65 standard deviations above the HP-detrended mean of the series. Data frequencies are monthly. Blue horizontal lines mark months of maximum volatility within a high-uncertainty period (the actual 'Bloom-Shocks'). All series apart from consumer uncertainty series (Michigan Survey) start in July 1962, Michigan Survey in March 1978.

2.3.2. Modeling Uncertainty Shifts

3. The Channels, *or*: The Micro-Macro-Nexus

While uncertainty in economics has been dealt with already long before the Great Recession, it is safe to say that research in the field surged in the past decade to put, among others, arguments that point at increased uncertainty as a compounding factor to the Great Recession and subsequent slow recovery on steadier grounds. This growing body of literature covers the entire spectrum including studies examining the matter from solely (i) purely theoretical, (ii) purely empirical or (iii) both perspectives in both micro- and macroeconomic analyses deploying and developing various uncertainty measures (see Section 2.1). In our review below we will refer to works falling into either of three categories whereby contributions having both an empirical and theoretical component are in a slight majority. Note, however that also purely theoretical or empirical works often pick up previous theoretical or empirical results that have been reported in the literature and thereby all the more establish a theory-empirics-nexus. Further, while the Great Recession is frequently mentioned as a reference, the implications of the results are often-times generalized without specific attribution to the Great Recession. At most, key economics features (e.g. zero lower bounds, etc.) are considered in model extensions.

A large body of the literature (both theoretical and empirical) studies potential channels through which macroeconomic uncertainty might alter economic agent's behavior both in PE and GE settings which in turn adversely affects economic activity. In particular, the literature largely discusses *real-options-*, *risk-aversion-* and *risk premia-effects* that affect investment, consumption and the access to finance. In both PE and GE settings (with additional frictions), time-varying uncertainty suggests to play a role.

The *real-options-effect* touches upon both firms (investment and hiring decisions) and households (consumption and thus saving decisions) and under certain conditions establishes the following results: For firms, the idea is that when being faced with uncertainty, firms become more cautious about investment and hiring if those decisions cannot easily be reversed (so-called 'investment adjustment costs') which is summarized under the *delay effect*.[1] Works in the field include, among others, Dixit and Pindyck (1994), Bernanke (1983)[READ!], Abel and Eberly (1996) and McDonald and Siegel (1986).[2] For effects on hiring see e.g. Bentolila and Bertola (1990).

Besides uncertainty affecting the *levels* of investment and hiring (the delay effect), theory suggests that economic agents also become *less sensitive* to changes in external conditions in an uncertain environment (the *caution effect*).[4] In this Bloom (2014) also sees an explanation for uncertainty stalling productivity growth due to an impediment to the productivity-enhancing reallocation of resources across firms (see also Bloom et al., 2012[READ!]).

On the consumption side, equivalent patterns arise (delay and caution effect) and lead to precautionary spending cutbacks: uncertainty causes households to reduce the consumption of durable goods (items with a high real option value under uncertainty) like houses, cars, etc. (see e.g., Eberly, 1994, Romer, 1990). Risk aversion might turn this precautionary spending effect into precautionary *savings* effect with a likely aggregate contractionary effect in the short run. While in theory (as mentioned by Bloom, 2014), consumption cutbacks and a higher saving rate may induce investment and growth in the longer term,

[1]These option-effects are alleviated, however, if, on the other hand, delays would be so costly as to hamper firm's ability to wait.

[2]Dixit and Pindyck (1994)[READ!], primarily looking at investment, introduce the "option value for better (but never complete) information" when it comes to investment decisions.[3] Bernanke (1983) investigates optimal investment decisions under uncertainty in an oil cartel and finds that high uncertainty causes firms to postpone investments and hiring in an environment where investment projects cannot easily be undone and labor market laws cause changes to the labor force (either hires or fires) to be costly.

[4]This result, among others, increases pressure on authorities to put forth monetary and fiscal interventions strong enough to outweigh these effects.

Fernandez-Villaverde et al. (2011) suggest that for a small open economy also potential positive long-run effects are impeded due to money fleeing the country. Likewise, in New Keynesian models they show that for large but more closed economies no positive savings (investment)-effects apply because through interactions between sticky prices (nominal rigidities) and search frictions missing market adjustments of interest rates and output prices might cause uncertainty shocks to translate into 'aggregate demand shocks' (see in particular Leduc and Liu, 2016 and Basu and Bundick, 2017).

Turning to financial markets, the idea is that frictions cause uncertainty to put upward pressures on the cost of finance by increasing risk premia due to investors' demand for an adequate risk-compensation. In addition, creditors might drive up interest rates and retract overall lending activity which further hampers firms' ability to borrow and in effect contracts investment and subsequently output (see e.g., Gilchrist et al., 2014[READ!], Christiano et al., 2014, Arellano et al., 2011)[READ!]. A potential additional precautionary effect studied in the literature is managerial risk aversion whereby under uncertainty investment decreases in particular for firms where the managers themselves hold a considerable amount of shares (see e.g. Panousi and Papanikolaou, 2012).

Besides the above mentioned detrimental effects of uncertainty, Bloom (2014) also mentions potential channels through which uncertainty can have a positive effect on growth in the long run. First, within the framework of real options the effects are not universal insofar as they are strongly subject to the condition of (ir)reversibility: if firms can easily adjust their behavior to allow for more flexibility under deteriorating circumstances the expected detrimental effects might be alleviated (see, e.g., Valletta and Bengali, 2013)[READ!]. Second,

Apart from the above mentioned literature, investigations into uncertainty go into many various directions. Among others (a non-exhaustive list), this and that and a literature on the linkage between this and that and so on....(MAYBE I SHOULD BETTER PUT THIS INTO A BIGGER FOOTNOTE WHERE I BRIEFLY MENTION OTHER STRNDS OF THE LITERATURE!) Example: Various studies look into particular types of uncertainty (e.g., effects of political uncertainty, etc.)......

Note to self:

- IMF-Paper: The impact of uncertainty differs across sectors and countries. The sectors that produce durable goods - including machinery and equipment, automobiles, houses, and furniture - are often the most affected by increases in uncertainty. The impact of an uncertainty shock on consumption and investment is larger in emerging market economies than in advanced economies, probably because the former group tends to have less developed financial markets and institutions (Carriere-Swallow and Cespedes, 2011). [...] High uncertainty tends to be associated with a lager drop in investment than in output and consumption growth. These findings lend support to the validity of different theoretical channels through which uncertainy adverseley affects economic adtivity.
  Policy-induced uncertainty is also negatively associated with growth. The adverse impact works mainly through two channels. [...] As noted, policy uncertainty has increased to record levels since the Great Recessions. Specifically, the increase in policy uncertainty between 2006 and 2011 was about 5 standard deviations. (see Baker, Bloom, and Davis (2012).).

- Baker et al. (2015, p. 1597) write: “Second, there is a literature focused explicitly on policy uncertainty Friedman (1968), Rodrik (1991), Higgs (1997), and Hassett and Metcalf (1999), among others, consider the detrimental economic effects of monetary, fiscal, and regulatory policy uncertainty. More recently, Born and Pfeifer (2014) and Fernandez-Villaverde et al. (2015) study policy uncertainty in DSEG models, finding moderately negative effects, while Pastor and Veronesi (2012, 2013) model the theoretical links among fluctuations, policy uncertainty, and stock market volatility. In other related work, Julio and Vook (2012) find that investment falls around national elections, Durnev (2010) finds that corporate investment becomes less responsive to stock prices in election years, Brogaard and Detzel (2015) find that policy uncertainty reduces asset returns, Handley and Limao (2015) find that trade policy uncertainty delays firm entry, Gulen and Ion (2016) find negative responses of corporate investment to our EPU index, Koijen et al. (2016) develop evidence that government-induced uncertainty about profitability generates a large equity risk premium for firms in the health care sector and reduces their medical R&D, and Giavazzi and McMahon (2012) find that policy uncertainty led German households to increase savings in the run-up to the close and consequential general elections in 1998.

Ferrara Guerin (2016) write: “While there are different ways to measure uncertainty, qualitatively, there seems to be a strong convergense of results concerning the effects of uncertainty shocks on macroeconomic activity[we should better call this AGGREGATES], regardless of the measure used in the empirical analysis.

The study whose results serve as a benchmark for our own analysis by replicating its empirical part in Section 4 below is Bloom (2009) who proposed uncertainty shocks as a 'new' driver of business cycles and triggered much of the literature in subsequent years. Bloom (2009) himself links his work to earlier publications of Bernanke (1983) and Hassler (1996) and conducts a comprehensive analysis of the impact of uncertainty shocks on business cycle fluctuations by (1) building a model with a time-varying second moment from which he simulates a macro uncertainty shock and (2) compares the results to the impulse response functions of vector autoregression (VAR) estimations on actual data. While the bulk of his work concentrates on the former, interestingly it is the latter (the empirical analysis using VARs) that has triggered much controversy in the literature. In particular, using 17 identified 'exogenous shocks' (which we have discussed in Section 2.3.1), in support of his theoretical model Bloom (2009) estimates VARs showing that an uncertainty shock in the data (the VXO-measure) produces a short-run drop in industrial production of 1% which lasts for about 6 months (a confirmation for the 'wait-and-see approach') and subsequently creates a longer-run overshoot. In his setting, these results are robust to the effect of an uncertainty shock on employment and a range of alternative approaches (including variable ordering, variable inclusion, shock definitions, shock timing, and detrending).

I should describe the terms before discussing the various papers: SEARCH FRICTIONS –> isolated description of search-frictions (Leduc and Liu (2016) write: "Indeed, in our model with search frictions, uncertainty shocks can be contractionary even with flexible prices, in contrast to the real business cycles (RBC) model with a spot labor market.): Leduc and Liu (2016) write: "Search frictions provide an additional mechanism for uncertainty shocks to generate large increases in unemployment via an option-value channel. With search frictions, a job match represents a long-term employment relationship that is irreversible. When times are uncertain, the option value of waiting increases and the match value declines. Firms respond by reducing hiring. This option-value effect in our model with search frictions arises for a similar reason as in the literature of irreversible investment decisions under uncertainty (Bernanke (1983); Bloom (2009); Bloom et al. (2012)."

NOMINAL RIGIDITIES/STICKY PRICES –> isolated description of search-frictions: Leduc and Liu (2016) write: Nominal rigidities are a key ingredient of many uncertainty studies because they "help amplifying the effect of uncertainty shocks on the unemployment rate through declines in aggregate demand. In addition, with sticky prices (i.e., nominal rigidities), inflation falls as aggregate demand declines, in line with our evidence."

Bachmann and Bayer (2013) ....

Baker et al. (2015) ....

Bloom et al. (2012) .... Bloom, Foetotto, Jaimovich, Saporta-Eksten, and Terr (2014) read –> add a summary about it here!

Bloom (2009).............

Bachmann et al. (2013)........

Born and Pfeifer (2014)

Jurado et al. (2015)...........

Fernandez-Villaverde et al. (2011) ......

Schaal (2017)...........Leduc and Liu (2016) refer to Schaal (2017) when they write about their findings regarding the interplay between nominal rigidities and search frictions: "This finding is consistent with Schaal (2017), who studies a search model with flexible prices. He obtains sizable effects from idiosyncratic volatility shocks - his measure of uncertainty - but partly by assuming that these volatility shock are negatively correlated with the level of aggregate productivity. Instead, when the option-value channel and the demand channel are simultaneously operating, as in our model, they interact to amplify the effects of uncertainty shocks and generate unemployment responses that are broadly in line with the data."

Stating their relation to the literature, Leduc and Liu (2016) refer to Bloom (2009), Bloom et al. (2012), Jurado et al. (2015), Scotti (2016), Bachmann et al. (2013) and Fernandez-Villaverde et al. (2011) when they write: "On the empirical side, we document a new stylized fact that uncertainty acts like a negative aggregate demand shock that raises unemployment and lowers inflation. [...] Our empirical approach thus complements those in the literature, where uncertainty is measured using cross-sectional dispersions of earnings or productivity at the firm or industry levels (Bloom (2009); Bloom et al. (2012)), the conditional variance of the unforecastable component in statistical models (Jurado et al. (2015); Scotti (2016)), forecast disagreements (Bloom (2009); Bachmann et al. (2013)) or the volatility of fiscal instruments estimated under time-varying volatilites (**?**–> will not read!).

Leduc and Liu (2016) write: "On the theory side, we show that an uncertainty shock can generate the observed demand-like macroeconomic effects through interactions between an option-value channel stemming from search frictions and an aggregate demand channel associated with nominal rigidities. Our model complements the recent theoretical literature on the macroeconomics effects of uncertainty. This strand of literature is too vast to enumerate (see Bloom (2009), Gilchrist et al. (2014), Arellano et al. (2011), Basu and Bundick (2017), Bloom et al. (2012), Born and Pfeifer (2014) –> see Bloom (2014) for an overview.).
While Born and Pfeifer (2014) don't find convincing evidence for large real effects of policy uncertainty shocks in a standard DSGE model, Leduc and Liu (2016) find that uncertainty shocks produce effect similar to aggregate demand shocks. To highlight aggregate demand effects (and abstracting from additional features that would also shed light on effects on investment), their theoretical DSGE framework incorporates both search frictions and nominal rigidities as key ingredients where the interplay of the reciprocal amplification of an option-value channel arising from search frictions in the labor market and decreases in aggregate demand stemming from sticky prices in the goods market produces a transmission mechanism of uncertainty on unemployment and inflation that is consistent with their empirical observation.[5] Specifically, their theoretical model is guided by the empirical evidence derived from a four-variable Bayesian VAR (BVAR) on US data consisting of a measure of uncertainty, the unemployment rate, the CPI year-on-year inflation rate and a short-term interest rate (as represented by the three-month Treasury bills rate). In this setting, the

[5] Under existing search frictions that reduce the value of a new match and cause firms to reduce hiring which drives up unemployment and ultimately reduces aggregate demand, when additionally prices are sticky, an increase in uncertainty also leads to a decline in aggregate demand which reinforces the option-value channel and generates an increase in unemployment. Under existing nominal rigidities the effect of decreasing aggregate demand is amplified when adding search frictions because the value of a new match decreases even further which ultimately pushes up the unemployment rate which in turn reduces households' income even further and aggravates the reduction in aggregate demand. This interaction considerably amplifies the fall in aggregate demand in response to uncertainty shocks in comparison to standard DSGE models that solely consider nominal rigidities and go without search frictions as in e.g. Basu and Bundick (2017).

authors declare the observed joint dynamics of sharply rising unemployment and decreasing inflation following an uncertainty shock to resemble features of a negative aggregate demand shock.[6] Contrary to the sole usage of the VIX as an uncertainty measure, Leduc and Liu (2016) report the dynamics to be robust to their alternative uncertainty measure of consumers' perceived uncertainty derived from the Thomson Reuters/University of Michigan Surveys of Consumers.[7] Their rationale for using a consumer uncertainty measure is that, by construction of the survey, interviewees do not have (complete) information of the current month's macroeconomic data. Hence, it is assumed that survey participants will condition their answers on all previous realizations of macroeconomic indicators except time t.[8] The resulting IRFs at impact of an uncertainty shock show a strongly persistent unemployment increase, peaking after approx. 18 months and significantly lasting for about three years. Inflation shoots in the opposite direction with a peak effect after around 20 months and staying significant for almost two years.[10]

Based on the empirical evidence of a VAR including the VXO as a measure of uncertainty, gross domestic product (GDP), consumption, investment, hours worked, the GDP deflator, the M2 money stock, and a measure of the monetary policy stance (in that order) over the 1986-2014 sample period[11], Basu and Bundick (2017) argue for the resulting co-movement of output, consumption, investment, and hours worked to be a key empirical feature of an economy's

[6]Adding habit formation to their model, their calibrated DSGE model comes closest to the empirical results from the VAR-model.

[7]Due to data availability of the respective uncertainty measures, their estimation window accordingly covers 01/1978 - 10/2013 for the model containing the consumers' perceived uncertainty and 01/1986 - 10/2013 in case of the VIX.

[8]Placing the uncertainty measure first in their Choleski ordering hence implies that on impact of a shock only unemployment, inflation and the nominal interest rate are allowed to respond. With their identification strategy Leduc and Liu (2016, p. 23) assume that their "[...] measured uncertainty contains *some*[9] exogenous component and does not reflect endogenous responses of other macroeconomic variables.

[10]To accomodate the zero lower bound (ZLB) in U.S. monetary policy after 2008, Leduc and Liu (2016) report their VAR to also be robust to the usage of the two-year Treasury bond yield (that did not reach the ZLB) as an alternative indicator of the monetary policy stance. To accomodate the possibility of survey respondents' perceptions of bad economic times instead of uncertainty about the future, Leduc and Liu (2016) follow a similar approach like Baker et al. (2015) and add a variable for consumer sentiment as an additional control to their BVAR. The results suggest that uncertainty is indeed forward-looking.

[11]All variable apart from the monetary policy measure enter the VAR in log levels.

(i.e., the data's) response following an uncertainty shock and hence also as a "[...] key minimum condition that business-cycle models driven by uncertainty fluctuations should satisfy" (Basu and Bundick, 2017, p. 937).[12] Identifying the uncertainty-shock using a Cholesky decomposition with the VXO ordered first, the authors assume that uncertainty shocks can affect output and its components immediately but that non-uncertainty shocks, however, do not influence the VXO on impact. With this ordering, their VAR generates statistically significant co-moving declines in output, consumption, investment, and hours worked with a peak response after approximately one year whereby their key stylized fact is robust to several modifications.[13] These insights are subsequently brought into a DSGE model (non-competitive, one-sector closed-economy model) where they calibrate their uncertainty shock process using fluctuations in the VXO and add nominal price rigidities (sticky prices) to replicate the transmission mechanism which was identified in the data. According to Basu and Bundick (2017), the resulting dynamics due to the incorporated price rigidity in a model where output is demand-determined are able to support the intuition that an increase in uncertainty which induces precautionary savings, reduces household expenditures, output and labor input and eventually the demand for capital and investment as suggested by their VAR-model.

Contrary to Bloom's findings, Jurado et al. (2015) and Bachmann et al. (2013) using their own forecast-based measures (see Section 2.1.4) find a rather different response-pattern: their VARs show a sharp reduction in output at impact whose effect is far more persistent lasting for a couple of years after the shock with no signs of the overshooting effect as in Bloom (2009).

Note to self:

- Ferrara Guerin (2016) write: "While there are different ways to measure uncertainty, qualitatively, there seems to be a strong convergense of results concerning the effects of uncertainty shocks on macroeconomic activity[we should better call this AGGREGATES], regardless of the measure used

[12] At the same time, they see this feature as missing from the related work of Bloom (2009), Bachmann and Bayer (2013) or Gilchrist et al. (2014).

[13] These modifications include: inclusions of stock prices in the VAR (as is done e.g., by Bloom (2009)), measurement of uncertainty using the VIX instead of the VXO, a re-ordering of the VAR placing uncertainty last or an adjustment of the sample period to exclude the Great Recession.

in the empirical analysis.

- Baker et al. (2015, p. 1597) write: "This article relates to at least three strands of literature. Recent empirical papers include Bloom (2009), Bachman et al (2013), Bloom et al. (2014) and Scotti (2016) with a review in Bloom (2014).

- IMF-Paper: Empirical evidence based on VAR models points to a significant neagtive impact of uncertainty shocks on output and epmloyment. (Bloom 2009, Hirata and others, 2012). These results also echo the findings in a broader area of reserach on the negative impact of macroeconomic and policy volatility on economic growth (Ramey and Ramey, 1995); Kose, Prasad and Terrones, 2006).

Auch, wenn wir dann die Literatur zusammenfassen: alles richtig einbetten in meine Auseinandersetzung. Nicht einfach nur beschreiben, was in den Papern drinnensteht, sondern wie das related zu dem was ich bringe. Jeder Absatz der drinnensteht, muss einen Grund haben, warum er drinnensteht im Hinblick auf die Fragestellung usw.

Also: wohldefinierte Fragestellung, überschaubare Methode, Resultate. Das sollten die Kernkompetenzen sein (dass alles sauber beschrieben ist und zugänglich abgebildet ist, dass man weiß woher die Daten kommen und alles replizierbar ist).

As formulated by Bontempi et al. (2016, p. 24), the results found in the literature to date raise the following questions:

1. are uncertainty shocks temporary or more persistent?
2. is the degree of persistence of identified negative uncertainty effects related to the econometric specification and/or the particular uncertainty measure used?
3. does the time span over which a model is estimated play any role?
4.
5. Baker et al. (2015, p. 1595) write: "In Section IV we provide evidence of how firm-level and aggregate outcomes evolve in the wake of policy uncertainty movements. Causal inference is challenging, because policy

> responds to economic conditions and is likely to be forward looking. To make progress we follow a micro and a macro estimation approach. [...] Our second approach fits vector autoregressive (VAR) models to U.S. data. [...] The U.S. VAR results indicate that a policy uncertainty innovation equivalent to the actual EPU increase from 2005-2006 to 2011-2012 foreshadows declines of about 6% in gross investment, 1.1% in industrial production, and 0.35% in employment.

We want to discuss these questions in our penultimate Section 4 below.

works that combine empirics with theory and establish dsge-models in conjunction with empirical analysis on a micro or macro-level; I have to include this footnote somewhere where it makes sense.[14]

Besides theoretical approaches, one part of the empirical literature uses micro-data (mostly firm-level data) in an attempt to extract uncertainty effects

The growing body of recent empirical literature on the *potential* causal effects of time-varying economic uncertainty on macroeconomic activity (aggregates) qualitatively largely has one thing in common: in a VAR context, uncertainty shocks seem to have a negative effect on output (or proxies thereof such as industrial production or employment). But as summarized by Bontempi et al. (2016, p. 23), "[...] this key finding is only robust in regard to the uncertainty impact in the short run, whereas in the long run different works [using different uncertainty proxies and slight modifications in the econometric specifications] have pointed to somewhat heterogeneous output responses."

[14] A non exhaustive list of selected works includes, for example, Ramey and Ramey (1995), Aghion et al. (2005), Mills (2000) and Imbs (2007) on the relationship of volatility and growth, Leahy and Whited (1996) and Bloom et al. (2007) on the effect of uncertainty on investment, Barlevy (2004) and Gilchrist and Williams (2005) on the effects of uncertainty on business cycles, etc.

4. Empirical Analysis: Effects of Uncertainty on the U.S. Economy

Note to self:

- as written in the Appendix of Basu and Bundick (2017, p. 5): "As we discuss in the main text, the Federal Reserve hit the zero lower bound on nominal interest rates at the end of 2008. While we model this outcome rigorously using our theoretical model, it is less clear how to model the stance of monetary policy during our 1986-2014 sample period econometrically. [...] If we use the 1962-2008 sample of Bloom (2009) with the federal funds rate as the measure of monetary policy, our stylized fact remains: Higher uncertainty generates declines in output, consumption, investment, and hours worked.
- In line with the mainstream perspective and for the purpose of this work, we will elaborate below whether or not we can reasonably argue that the measures of uncertainty that we look at can indeed be regarded as exogenous sources of shocks within our empirical model.
- Here in the introduction to the Empirical Analysis I should outline the intuition behind the benchmark-model that we are analyzing (Bloom (2009)) which Bachmann et al. (2013) describe very well in their introduction to Section 2: "Time-varying uncertainty at the firm level may have economic consequences when there is a degree of irreversibility to firm actions. For a concrete example, suppose that a firm faces fixed costs to adjusting the size of its labor force and/or physical capital stock. Suppose further that there is a mean-preserving spread on the distribution of future demand for the firm's product. With fixed adjustments costs, higher uncertainty over future demand makes new hiring and investment less attractive. The reason for this is intuitive - if a large fixed cost must be paid do adjust the firm'S labor or capital, then there is reason to minimize the number of times this cost must be paid. If the future is very uncertain (in the sense that demand could be either very high or very low relative to the present), then it makes sense to wait until the uncertainty is resolved to undertake new hiring and investment." –> "An increase in uncertainty thus makes inaction relatively more attractive."

We now want to devote the rest of this thesis to the study of the dynamic relationships between and responses of a set of key macroeconomic variables to innovations (we'll call them 'shocks' in the following) of the various uncertainty measures which we have introduced in Section 2. Various models have been suggested/studied in the literature each of them suggesting a slightly different set of variables to include and/or ordering with which the variables enter the VAR. For us, the benchmark model with which we will start is Bloom (2009) (see Section 4.1), followed by a macro VAR in the style of Christiano et al. (2005)

4.1. The Benchmark Model: VAR-8 following Bloom (2009)

The starting point of our estimations are VARs that Bloom (2009) used in his original contribution. The ordering as depicted in vector 4.1 below according to Bloom (2009, p. 630) is based on the assumptions that shocks instantaneously influence the stock market (levels and volatility), then moves on to prices (wages, the consumer price index (CPI), and interest rates), and finally eventually affects quantities (hours, employment and output). In particular, Bloom (2009)'s rationale for including the stock-market levels as the first variable in the ordering is to ensure that the impact of stock-market levels is already controlled for when looking at the impact of volatility shocks. Further, Bloom (2009) detrends all variables that enter the VARs using the HP-filter (Hodrick and Prescott, 1997) apart from the uncertainty measure(s).[1]

Jurado et al. (2015) replicate Bloom (2009)'s VARs in their contribution, renounce to detrend the variables however, arguing that the HP filter uses information over the entire sample which makes it difficult to interpret the timing of an observation and report results using Bloom (2009)'s original detrended

[1] In vector 4.1 all variables that enter the VAR detrended are marked with a *c*-prefix to indicate that the variable denotes the remaining cycle-component after removal of the trend.

variables in their Appendix.

$$\text{VAR-8:} \begin{bmatrix} \text{c-log(S\&P500 Index)} \\ \text{uncertainty} \\ \text{c-federal funds rate} \\ \text{c-log(wages)} \\ \text{c-log(CPI)} \\ \text{c-hours} \\ \text{c-log(employment)} \\ \text{c-log(industrial production)} \end{bmatrix}, \begin{bmatrix} \text{log(S\&P500 Index)} \\ \text{uncertainty} \\ \text{federal funds rate} \\ \text{log(wages)} \\ \text{log(CPI)} \\ \text{hours} \\ \text{log(employment)} \\ \text{log(industrial production)} \end{bmatrix} \tag{4.1}$$

In Figure 9 below we have plotted the (orthogonalized) impulse response functions (IRFs) to orthogonal shocks created from a Cholesky decomposition for the VAR-8 setting according to Bloom (2009)'s original contribution (i.e., all variables apart from the uncertainty measures detrended). While Bloom (2009) solely considers the VXO/volatility-series (and derived shock-measures in various flavors - one of which, the month with the maximum volatility in a series of months with extraordinarily high volatility, we call 'Bloom-Shock' here) as his uncertainty measure with its effect on industrial production (as a proxy for output) and employment, in the spirit of Jurado et al. (2015) and Bontempi et al. (2016) we here report a full bank of IRFs for the selection of popularized uncertainty measures we have discussed in Section 2.1: the original 'Bloom-shock' and the VXO/volatility-series (as used by Bloom, 2009), the MSoC (as used by Leduc and Liu, 2016), the EPU (as used by Baker et al., 2015), the GTU (as used by Bontempi et al., 2016 and Castelnuovo and Tran, 2017) and finally the macro uncertainty index as introduced by Jurado et al. (2015).

have to write into the caption that the length of the availability of the uncertainty measure is the limiting factors in all VARs (so for the macro uncertainty index, accordingly all data runs from 1960 until 2018, for the EPU from 1985 until 2018, for the GTU from 2004 to 2018 etc., etc.!!!)

A good sentence: 'The effect on impact, in contrast, is small.' Ein Satz aus

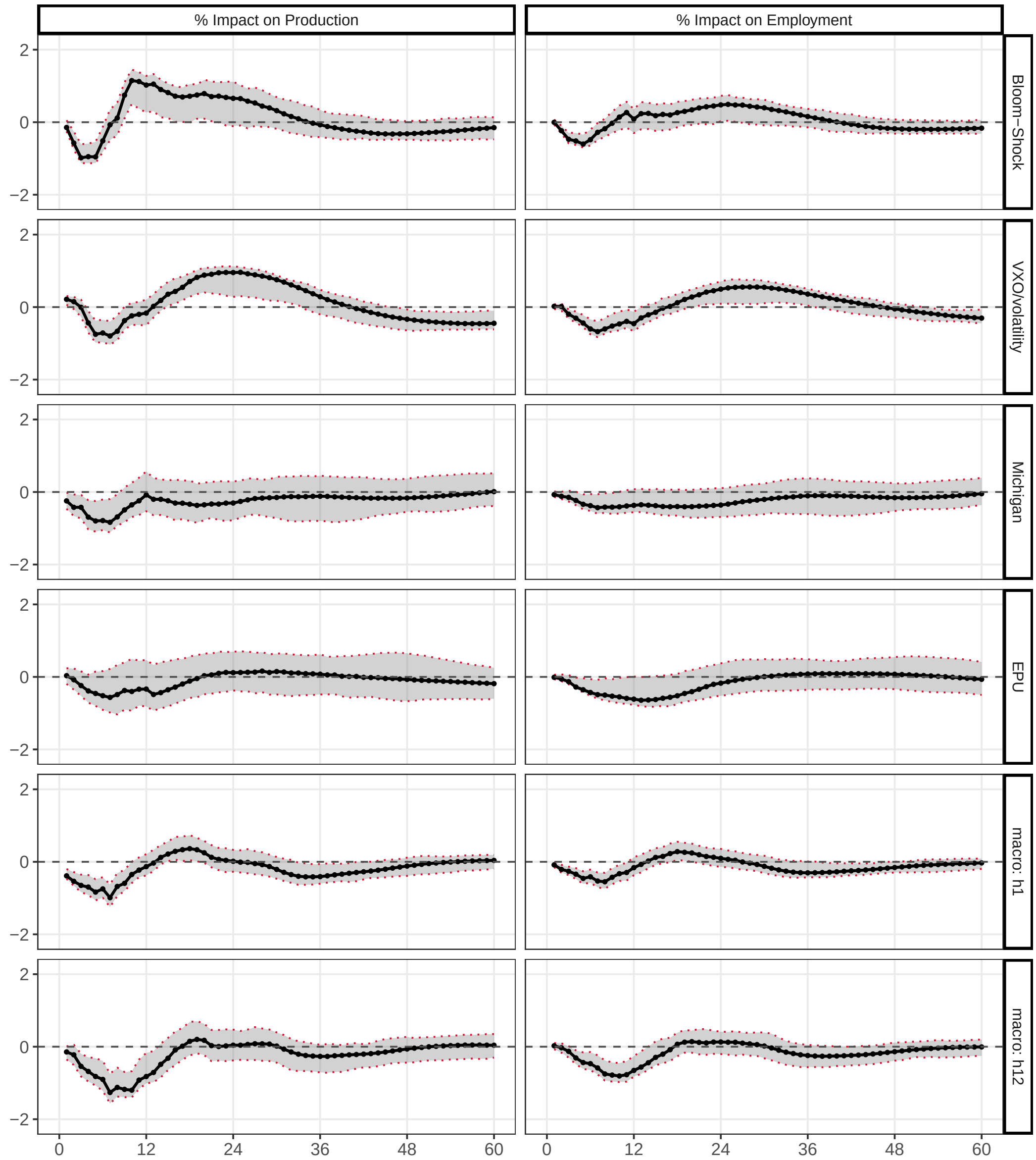

Figure 9.: Impulse Response Functions of Production and Employment from Estimations of VAR-8 following Bloom (2009) using all uncertainty measures. Variables enter the VAR-8 according to 4.1.
Note: Dashed lines show 68% standard error bands. The data are monthly and span the period 1962:07-2008:06 for the Bloom-Shock and VXO/volatility series, 1978:02-2008:06 for the MSoC uncertainty series, 1975:01-2008:06 for the EPU and 1962:07-2008:06 for the Macro Uncertainty Index (both $h = 1$ and $h = 12$).

Bachmann, den ich für meine eigene Arbeit verwenden sollte: "The next sectino discusses the wait-and-see mechanism and delivers a benchmark against which we compare our empirical results." (p. 4) –> Then I can replicate the results from Bloom and then show the results that local projections would produce.

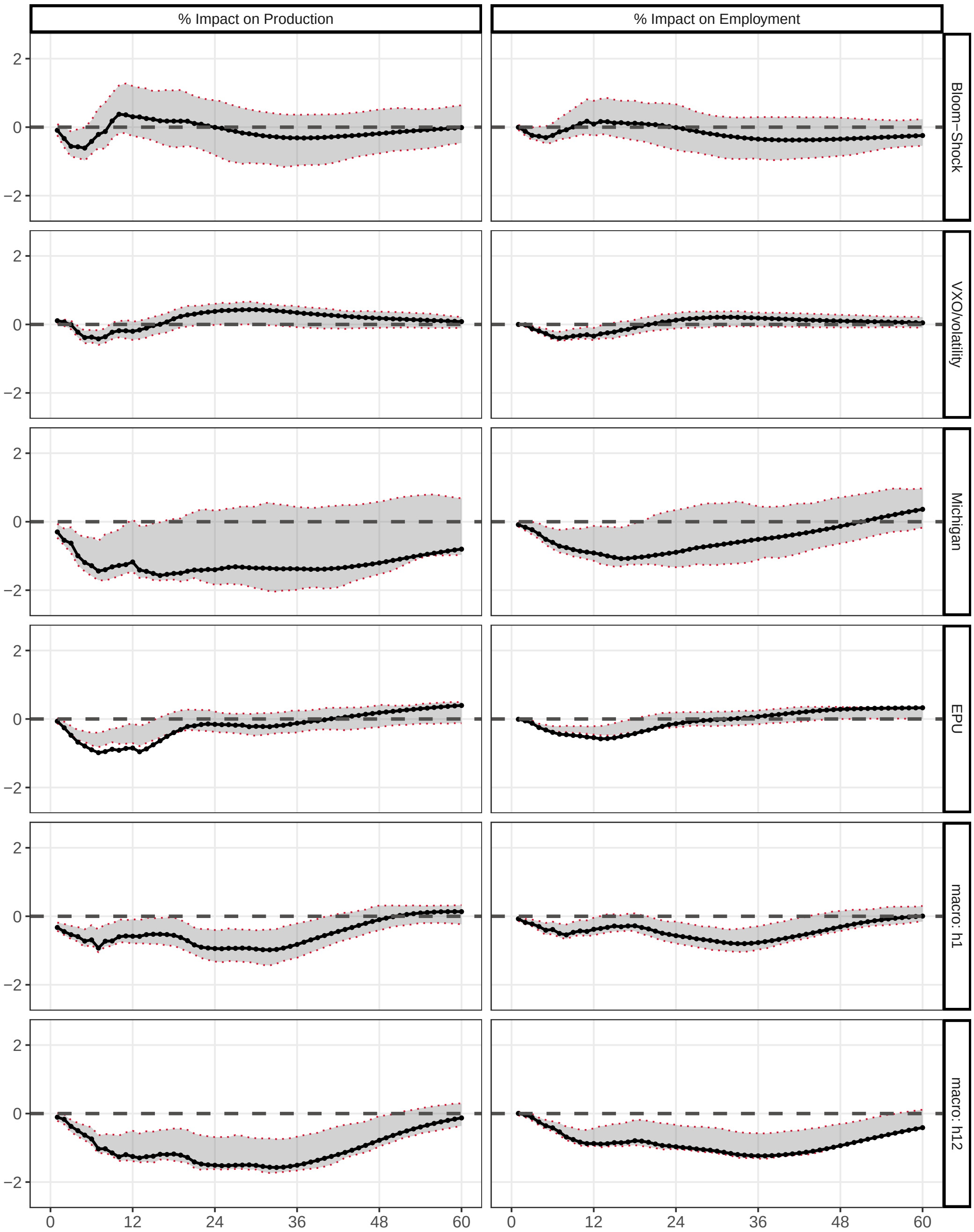

Figure 10.: Impulse Response Functions of Production and Employment from Estimations of a modified version of the VAR-8 Bloom (2009) using all uncertainty measures. Variables enter the VAR-8 according to 4.1.

Note: Dashed lines show 68% standard error bands. The data are monthly and span the period 1962:07-2008:06 for the Bloom-Shock and VXO/volatility series, 1978:02-2008:06 for the MSoC uncertainty series, 1975:01-2008:06 for the EPU and 1962:07-2008:06 for the Macro Uncertainty Index (both $h = 1$ and $h = 12$).

Note to self: Bachmann et al. (2013) write on p. 5: "In this section we give a brief overview of the "wait-and-see" mechanism that might give rise to uncertainty-driven fluctuations. In addition to providing a benchmark against

which we can compare our empirical results, this exercise will also serve to motivate the use of high-frequency, sectoral data in examining the impact of uncertainty on economic activity."
Another sentence that Bachmann et al. (2013) use on p. 6: "Figure 2 provides an example of an impulse response of output to an increase in uncertainty, replicated from the model in Bloom (2009).

4.2. Alternative Estimations I: VAR-11 following Christiano et al. (2005)

As mentioned by Jurado et al. (2015) in their own estimations, Christiano et al. (2005)'s studied VAR has the advantage of consisting of a set of variables whose dynamic relationships have been well studied/established in the literature. But because in their original contribution, Christiano et al. (2005) use quarterly data, Jurado et al. (2015) apply a slightly modified version of Christiano et al. (2005)'s VAR to cover roughly the same sources of variation in the economy. This results in an 11-variable VAR whose ordering mimics the original model of Christiano et al. (2005) as depicted in vector 4.2:

$$\text{VAR-11:} \begin{bmatrix} \text{c-log(real IP)} \\ \text{c-log(employment)} \\ \text{c-log(real consumption)} \\ \text{c-log(PCE deflator)} \\ \text{c-log(real new orders)} \\ \text{c-log(real wage)} \\ \text{c-hours} \\ \text{c-federal funds rate} \\ \text{c-log(S\&P500)} \\ \text{c-growth rate of M2} \\ \text{uncertainty} \end{bmatrix}, \begin{bmatrix} \text{log(real IP)} \\ \text{log(employment)} \\ \text{log(real consumption)} \\ \text{log(PCE deflator)} \\ \text{log(real new orders)} \\ \text{log(real wage)} \\ \text{hours} \\ \text{federal funds rate} \\ \text{log(S\&P500)} \\ \text{growth rate of M2} \\ \text{uncertainty} \end{bmatrix} \tag{4.2}$$

4.3. Alternative Estimations II: Local Projections following Jordà (2005)

In his original estimations, Bloom (2009) estimates a range of VARs including the variables log(S&P 500 stock market index), a stock-market volatility indicator (the 'Bloom-shocks' we have constructed above!), the Federal Funds Rate, log(average hourly earnings), log(consumer price index), hours, log(employment), and log(industrial production). Thereby all variables are HP detrended in the baseline estimations.
Instead, we use the Jordà (2005) local projection method to estimate impulse responses which estimates regressions of the dependent variables at horizon $t + h$ on the shock in period t and uses the coefficient on the shock as the impulse response estimate.

The estimated series of regressions looks as follows:[2]

$$z_{t+h} = \alpha_h + \theta_h \text{shock}_t + \text{control variables} + \epsilon_{t+h} \tag{4.3}$$

In the above specification, z_{t+h} is the variable of interest (in our case we look at industrial production and employment in manufacturing), the control variables include the log of the S&P500 stock market index, the Federal Funds Rate and three lags of the dependent variable z itself and the shock refers to the 'Bloom-shock' which we have constructed above.[3] For the series of regressions we look five years ahead, i.e., estimate 61 regressions using monthly data (starting to count at $h = 0$). The coefficient θ_h gives the response of the dependent variable z at time $t + h$ to the shock at time t. And because the ϵ_{t+h} will be autocorrelated, the standard errors must be HAC, i.e. *hereoskedasticity and autocorrelation consistent*.
The data-sources are described in Appendix B.1

[2]Note an Hans: die Spezifikation wird natürlich noch überarbeitet. Ist nur eine baseline, um den code zu implementieren.

[3]All variables are HP-detrended.

Figures 11 and 12 plot the preliminary responses of industrial production and employment (in manufacturing) to a shock at time t.

Note to self:

- as compared to Bloom (2009), we already see a different pattern (BUT: we have not yet fully 'translated' the model or replicated the data-generating process that Bloom (2009) assumes (see next point below).
  In particular, as formulated by Bachmann et al. (2013), 'we find that innovations to business uncertainty are associated with small and slowly-building reductions in economic activity'.
- guter Satz aus Bachmann et al. (2013), p. 15: "Figure 3 provides corroborating evidence with a different measure of sectoral economic activity."
- Bachmann et al. (2013), p. 17: "Wait-and-see theories of the transmission from uncertainty shocks to business cycles emphasize hiring and firing frictions. If the 'wait-and-see' - channel were important, we would observe a large reduction in employment followed by a quick recovery in response to an uncertainty shock, similarly to the output response in Figure 2 in Section 2 (the Bloom-figure)."
- weitere guter Satz aus Bachmann et al. (2013), p. 17: "However, the response of manufacturing employment is rather consistent with our other results: it moves little on impact, followed by a period of sustained reductions, with no obvious tendency for reversion, even at very long horizons."
  Note to self: contrary to their finding, we DO FIND A TENDENCY FOR REVERSION AT THE LONG HORIZON!
- bezüglich das DGP: wie sollte unsere Spezifikation aussehen um möglichst nahe an den von Bloom unterstellten DGP ranzukommen? Mit anderen Worten: Wie 'übersetzt' man einen VAR in local projections?

Note to self:

- "Real GDP has the virtue of being the broadest indicator of real economic activity. Its downside is that it is difficult to measure [...]. For this reason, we also consider two other indicators: industrial production and the unemployment rate. Industrial production has the benefit of being relatively straightforward to measure; unemployment has the benefit of being perhaps the closest to a purely cyclical indicator." (Romer & Romer, p. 3092)
- Footnote 17 in Romer and Romer (2017): "The impulse response functions in Figure 4 are estimated using the Jordà local projection method. Figure C2 of online Appendix C shows that the results estimated using a conventional vector autoregression are virtually identical." –> should we include a comparison with Bloom's VAR?
- Romer and Romer (2017, p. 3096): "To do this, we run the same regression as in equation (1), but with our new measure of financial distress as the dependent variable. Since by construction the response of distress to itself is one at t = 0, we only estimate the regression for horizons 1 to 10. This analysis shows that distress is very serially correlated, particularly at near horizons. This

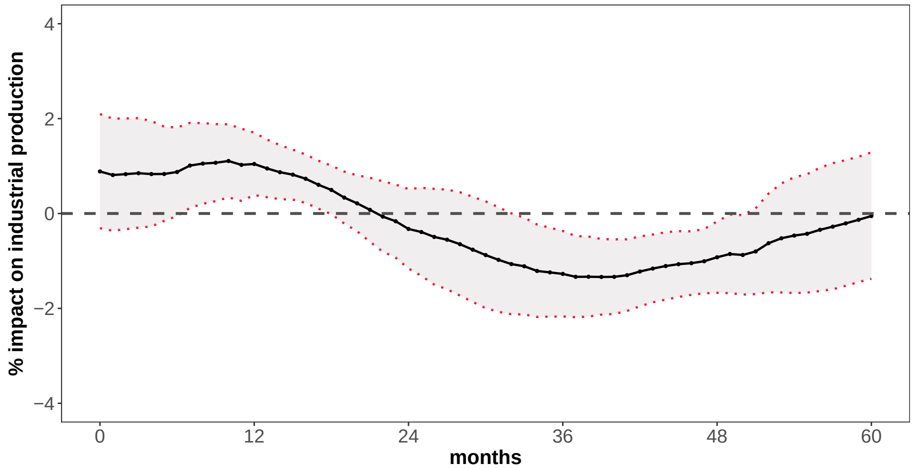

Figure 11.: Local projection estimations of the impact of a volatility shock on industrial production. *Note:* Dashed lines are 1 standard-error bands around the response to a volatility shock.

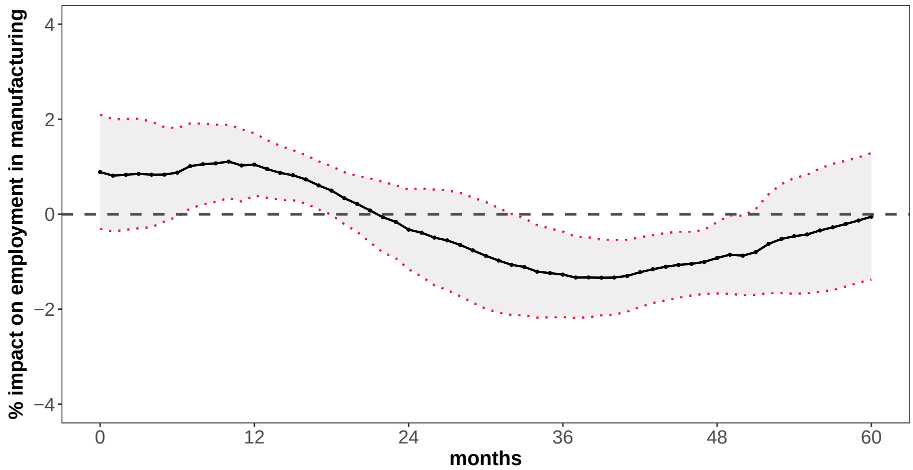

Figure 12.: Local projection estimations of the impact of a volatility shock on industrial production. *Note:* Dashed lines are 1 standard-error bands around the response to a volatility shock.

finding suggests that some of the near-term persistence we find in the negative aftermath of financial distress is likely due to persistence in distress itself. It is not necessarily that financial crises have long-lasting effects, but rather that crises themselves tend to last for a while. This possibility [...] is analyzed further in Section III."

- Romer and Romer (2017, p. 3097): "Given that our new series on financial distress differs in important ways from existing crisis chronologies, it is useful to compare our findings for the average aftermath of financial crises with those estimated using the other series." –> We can use this approach similarly by using various uncertainty measures in our regressions as alternative and compare the impulse-response functions.

- Romer and Romer (2017, p. 3099), *Dealing with Heteroskedasticity*: "The first issue is possible differences in the variance of the residuals across countries. Economic activity is typically much more volatile in the less developed countries in our sample (such as Greece and Turkey), and in the smaller countries. It is plausible to think that the variances of the residuals in equation (1) also vary systematically by country.
–> Taking into account heteroskedasticity in the residuals has a substantial impact on the estimates. Though the time pattern of the decline in GDP is relatively unchanged, the maximum decline is reduced by about one-third."

- Romer and Romer (2017, p. 3010): "In a related exercise, we also consider alternatives to conventional standard errors. In addition to heteroskedasticity of the residuals, there may also be serial correlation due to the overlapping structure of the residuals. We therefore experiment with both heteroskedasticity-consistent standard errors, and two forms of heteroskedasticity- and serial-correlation-corrected standard errors. Table C1 of online Appendix C shows that the alternative standard errors are typically about 30 to 50 percent larger than conventional standard errors. Thus, using the alternatives reduces the statistical significance of the estimated negative aftermath of a financial crisis substantially. Nonetheless, the estimates for GDP remain statistically significant at standard levels at all horizons."

- Ramey and Zubairy (2018, p. 15): "The only complication associated with the Jordà method is the serial correlation in the error terms induced by the successive leading of the dependent variable. Thus, we use the Newey-West correction for our standard errors (Newey and West, 1987)."

- Ramey and Zubairy (2018, p. 16): "Later, we will be comparing our baseline estimated to those from a threshold VAR." (–> This is something that we can maybe do as well; see a comment added above already!)

- Ramey and Zubairy (2018, p. 23), footnote 20: "We only estimate multipliers out five years because the Jordà method is less reliable at long horizons."

- When it comes to describing the data sources I should have a look at the way how Ramey and Zubairy (2018) explain each series in the Appendix.

- Ramey (2016, p. 17): "If the VAR adequately captures the data generating process, this method is optimal at all horizons. If the VAR is misspecified, however, then the specification errors will be compounded at each horizon. To address this problem, Jordà (2005) introduced a *local projection* method for estimating impulse responses."

- Ramey (2016, p. 18): "The control variables need not include the other $Y's$ as long as ϵ_{1t} is exogenous to those other Y's. Typically, the control variables include deterministic terms (constant, time trends), lags of the Y_i, and lags of other variables that are necessary to "mop up";
One estimates a separate regression for each horizon and the control variables do not necessarily

need to be the same for each regression. Note that except for horizon $h = 0$, the error term ξ_{t+h} will be serially correlated because it will be a moving average of the forecast errors from t to $t+h$. Thus, the standard errors need to incorporate corrections for serial correlation, such as a (Newey and West, 1987) correction.

- Ramey (2016, p. 37): The term "troughs" is very often used in the context of impulse response functions. Here an example sentence: "Industrial production begins to fall in the next month and roughs 21 months later." Literally translated it means "tief fallen" (auf sein tiefstes Niveau fallen). Another interesting expression is used on p. 39: "[...] until they bottom out during the fourth year after the shock."

- Ramey (2016, p. 45): "Why does the Jordà method give such different estimates from the proxy SVAR?" –> This is a question that I could actually elaborate on to possibly also compare our results investigating uncertainty using the Jordà method as opposed to the VAR that Bloom uses in his paper.

- In the presentation on the following web-page http://www.datavis.ca/courses/RGraphics/R-Graphics1.pdf on p. 35 I found an interesting way of plotting regression estimates! (instead of tables with standard errors, we plot the coefficients and confidence bands which let's the viewer immediately understand whether a coefficient is significantly different from zero or not.

4.3.1. Robustness Checks: Alternative Uncertainty Measures

This part provides results from a large number of robustness exercises designed to check the sensitivity of our results to various assumptions. (this sentence is formulated like this by Jurado et al. (2015)).

4.3.2. Interpretation of Results

Note to self:

- Jurado et al. (2015, p. 1181) write: "While we find that increases in uncertainty are associated with large declines in real activity, we caution that our results are silent on wehther uncertainty is the cause or effect of such declines. Our goal is to develop a defensible measure of time-varying macro uncertainty that can be tracked over time and related to fluctuations in real activity and asset markets. Our estimates do, however, imply that the economy is objectively less predictable in recessions thatn it is in normal times. This result is not a statement about changing subjective perceptions of uncertainty in recessions as compared to booms. Any theory for which uncertainty is entirely the effect of recessions would need to be consistent with these basic findings.

-

- Baker et al. (2015, p. 1596/1597) write: “Although our results are not necessarily causal, one plausible interpretation of our micro and macro evidence is that policy uncertainty retards investment, hiring, and growth in policy-sensitive sectors like defense, finance, healthcare, and construction, and these sectors are important enough for policy uncertainty to matter at the aggregate level.” –>
  In this report, on p. 20, the authors write:
  *“A basic challenge for policymakers is thus to move away from an incremental approach to policy-making and address the many downside risks to global activity with strong medium-term fiscal and structural reform programs in order to rebuild confidence. In the euro area, action is also needed to address the current crisis and, over the medium term, to complete the EMU.
  *Fiscal adjustment has become necessary in many cases to strengthen confidence in sovereign balance sheets and in many other cases because the prospects for future potential output—and hence revenue growth—are substantially less promising than they were before 2008. Unless governments spell out how they intend to effect the necessary adjustment over the medium term, a cloud of uncertainty will continue to hang over the international economy, with downside risks for output and employment in the short term. Fiscal adjustment should be gradual and sustained, where possible, supported by structural changes, as, inevitably, it weighs on weak demand.

5. Conclusion

In the article “Held Back by Uncertainty” Bloom and his Colleagues write: ” Policymakers can help.” –> I should build the conclusion up along these lines!

In Kose and Terrones, 2012 (How Does Uncertainty Affect Economic Performance"), p. 5, the authors write: “Policymakers can do little to alleviate the intrinsic uncertainty economies typically face over the business cycle. However, policy uncertainty is unusually high, and it contributes significantly to macroeconomic uncertainty. By implementing bold and timely measures, policymakers can reduce policy-induced uncertainty and help kick-start economic growth. What precisely policymakers need to do is discussed in the main text of Chapter 1:
There, the authors suggest:

A. Appendix

A.1. IRFs in a VAR-Setting

A.2. IRFs and Local Projections

A.3. Additional Tables

Table 5.: Comparison of uncertainty measures including shocks following identification methodology of Bloom (2009).
Note: High uncertainty periods are defined as periods where a series value is more than 1.65 standard deviations above the HP-detrended mean of the series (Bloom, 2009). Data frequencies are monthly. All series apart from consumer uncertainty series (Michigan Survey) start in July 1962, Michigan Survey in March 1978 and range until June 2008. Column 'ID' marks periods of continuously high uncertainty without interruption (considered a continuous block of 'shocks'), corresponding to an 'ID' the column 'label' marks periods *within* the same 'ID' as either 'f' (first month volatility in a continuous period) or 'm' (maximum volatility in a continuous period) or both (i.e., 'fm').

Date	Michigan	Label	ID	EPU Hist	Label	ID	Macro12	Label	ID	Macro1	Label	ID	VXO	Label	ID
Oct 1962													26	f m	1
Nov 1963													28.7	f m	2
Aug 1966													24.4	f m	3
Oct 1966													23.9	f m	4
Jan 1968				144	f m	1									
Mar 1968				123	f m	2									
May 1970													37.6	f m	5
Nov 1971				154	f m	3									
Jul 1973							1.02	f	1						
Aug 1973							1.04		1	0.79	f	1			
Sep 1973							1.04		1	8×10^{-1}		1			
Oct 1973							1.04		1	8×10^{-1}	m	1			
Nov 1973							1.04		1	0.79		1	28.8	f	6
Dec 1973							1.03		1	0.79		1	34.1	m	6
Jan 1974				160	f m	4	1.03		1	8×10^{-1}		1			
Feb 1974							1.03		1						
Mar 1974							1.03		1						
Apr 1974							1.03		1	0.79	f m	2			
May 1974							1.04		1						
Jun 1974							1.04		1						
Jul 1974							1.05		1	8×10^{-1}	f	3	29.8	f	7
Aug 1974							1.06		1	0.82		3	29.2		7
Sep 1974							1.06		1	0.82		3	36.8		7
Oct 1974							1.06		1	0.83		3	38.4	m	7
Nov 1974							1.06	m	1	0.85		3			
Dec 1974				162	f m	5	1.06		1	0.87	m	3			
Jan 1975							1.04		1	0.84		3			
Feb 1975							1.03		1	0.82		3			
Mar 1975										8×10^{-1}		3			
Jul 1979				175	f m	6									
Jan 1980							1.12	f	2						
Feb 1980							1.15		2	9×10^{-1}	f	4			
Mar 1980							1.18		2	0.95		4	29.2	f m	8
Apr 1980							1.21	m	2	1	m	4			
May 1980							1.21		2	0.98		4			
Jun 1980							1.2		2	0.95		4			
Jul 1980							1.18		2	0.95		4			
Aug 1980							1.17		2	0.93		4			
Sep 1980							1.16		2	0.91		4			
Oct 1980							1.15		2	9×10^{-1}		4			
Nov 1980							1.15		2	0.89		4			
Dec 1980							1.16		2	0.89		4			
Jan 1981							1.16		2	0.89		4			
Feb 1981							1.16		2	0.88		4			
Mar 1981							1.15		2						
Apr 1981							1.15		2						
May 1981							1.14		2						

Table 5.: Comparison of uncertainty measures including shocks following identification methodology of Bloom (2009).
Note: High uncertainty periods are defined as periods where a series value is more than 1.65 standard deviations above the HP-detrended mean of the series (Bloom, 2009). Data frequencies are monthly. All series apart from consumer uncertainty series (Michigan Survey) start in July 1962, Michigan Survey in March 1978 and range until June 2008. Column 'ID' marks periods of continuously high uncertainty without interruption (considered a continuous block of 'shocks'), corresponding to an 'ID' the column 'label' marks periods *within* the same 'ID' as either 'f' (first month volatility in a continuous period) or 'm' (maximum volatility in a continuous period) or both (i.e., 'fm').

Date	**Michigan**	**Label**	**ID**	**EPU Hist**	**Label**	**ID**	**Macro12**	**Label**	**ID**	**Macro1**	**Label**	**ID**	**VXO**	**Label**	**ID**
Jun 1981							1.15		2						
Jul 1981							1.14		2						
Aug 1981							1.13		2						
Sep 1981							1.13		2						
Oct 1981							1.13		2						
Nov 1981							1.12		2						
Jan 1982										0.88	f	5			
Feb 1982										0.88	m	5			
Aug 1982													32.4	f m	9
Oct 1982													32.8	f m	10
Nov 1982													32.4		10
Jan 1986				202	f m	7									
Oct 1987				236	f m	8							58.2	f m	11
Nov 1987				227		8							49.4		11
Dec 1987	5	f m	1	197		8							41.8		11
Jan 1988	5	m	1										38.3		11
Feb 1988													33.7		11
Sep 1990				195	f m	9							28.8	f	12
Oct 1990													30.1	m	12
Nov 1990	8.33	f	2	190	f m	10									
Dec 1990	11		2												
Jan 1991	11.7	m	2	242	f m	11									
Feb 1991	11.7	m	2												
Mar 1991	8.67		2												
Dec 1991	8	f	3	220	f m	12									
Jan 1992	10		3												
Feb 1992	10.3		3	190	f m	13									
Mar 1992	11	m	3												
Apr 1992	9.67		3												
May 1992	8.33		3												
Aug 1992	8.33	f	4												
Sep 1992	9.33		4												
Oct 1992	9.67	m	4	204	f m	14									
Nov 1992	8		4												
Nov 1997													31.5	f m	13
Aug 1998				176	f	15									
Sep 1998				216	m	15							39.2	f m	14
Oct 1998				193		15							37.5		14
Nov 2000				221	f m	16									
Dec 2000				2×10^2		16									
Jun 2001	5.33	f m	5												
Sep 2001	5.33	f	6	313	f m	17				0.78	f	6	42.7	f m	15
Oct 2001	7		6	288		17				0.79	m	6	34.5		15
Nov 2001	8	m	6	215		17				0.76		6			
Dec 2001	6		6												
Jan 2002				197	f m	18									
Jul 2002													38.5	f	16
Aug 2002													37.2		16
Sep 2002													41.7	m	16

Table 5.: Comparison of uncertainty measures including shocks following identification methodology of Bloom (2009).
Note: High uncertainty periods are defined as periods where a series value is more than 1.65 standard deviations above the HP-detrended mean of the series (Bloom, 2009). Data frequencies are monthly. All series apart from consumer uncertainty series (Michigan Survey) start in July 1962, Michigan Survey in March 1978 and range until June 2008. Column 'ID' marks periods of continuously high uncertainty without interruption (considered a continuous block of 'shocks'), corresponding to an 'ID' the column 'label' marks periods *within* the same 'ID' as either 'f' (first month volatility in a continuous period) or 'm' (maximum volatility in a continuous period) or both (i.e., 'fm').

Date	**Michigan**	**Label**	**ID**	**EPU Hist**	**Label**	**ID**	**Macro12**	**Label**	**ID**	**Macro1**	**Label**	**ID**	**VXO**	**Label**	**ID**
Oct 2002													41.4		16
Nov 2002				2×10^2	f m	19									
Jan 2003				230	f m	20									
Feb 2003	5.67	f	7										36.5	f m	17
Mar 2003	6.67	m	7	250	f m	21							35.2		17
Apr 2003	6.33		7	207		21									
May 2003	5.67		7												
Aug 2007													25.1	f m	18
Nov 2007													26.7	f m	19
Jan 2008				240	f m	22							28	f	20
Feb 2008													27.2		20
Mar 2008													29	m	20
Apr 2008	7	f	8												
May 2008	7.33	m	8							8×10^{-1}	f	7			
Jun 2008	6.67		8				1.04	f m	3	0.83	m	7			

Table 6.: Major Stock-Market Volatility Shocks. Replication of Table A.1 in Bloom (2009).

ID	Date Begin	Date End	Duration	Max Vol	First Vol	Date Max Vol	Date First Vol
1	Oct 1962	Oct 1962	1	26	26	Oct 1962	Oct 1962
2	Nov 1963	Nov 1963	1	28.7	28.7	Nov 1963	Nov 1963
3	Aug 1966	Aug 1966	1	24.4	24.4	Aug 1966	Aug 1966
4	Oct 1966	Oct 1966	1	23.9	23.9	Oct 1966	Oct 1966
5	May 1970	May 1970	1	37.6	37.6	May 1970	May 1970
6	Nov 1973	Dec 1973	2	34.1	28.8	Dec 1973	Nov 1973
7	Jul 1974	Oct 1974	4	38.4	29.8	Oct 1974	Jul 1974
8	Mar 1980	Mar 1980	1	29.2	29.2	Mar 1980	Mar 1980
9	Aug 1982	Aug 1982	1	32.4	32.4	Aug 1982	Aug 1982
10	Oct 1982	Nov 1982	2	32.8	32.8	Oct 1982	Oct 1982
11	Oct 1987	Feb 1988	5	49.4	40.8	Nov 1987	Oct 1987
12	Aug 1990	Oct 1990	3	30.1	27.8	Oct 1990	Aug 1990
13	Jan 1991	Jan 1991	1	26.9	26.9	Jan 1991	Jan 1991
14	Nov 1997	Nov 1997	1	31.6	31.6	Nov 1997	Nov 1997
15	Sep 1998	Oct 1998	2	39.2	39.2	Sep 1998	Sep 1998
16	Sep 2001	Oct 2001	2	42.6	42.6	Sep 2001	Sep 2001
17	Jul 2002	Oct 2002	4	41.7	38.5	Sep 2002	Jul 2002
18	Feb 2003	Mar 2003	2	36.5	36.5	Feb 2003	Feb 2003
19	Aug 2007	Aug 2007	1	25.1	25.1	Aug 2007	Aug 2007
20	Nov 2007	Nov 2007	1	26.7	26.7	Nov 2007	Nov 2007
21	Jan 2008	Mar 2008	3	29	28.1	Mar 2008	Jan 2008

A.4. Additional Figures

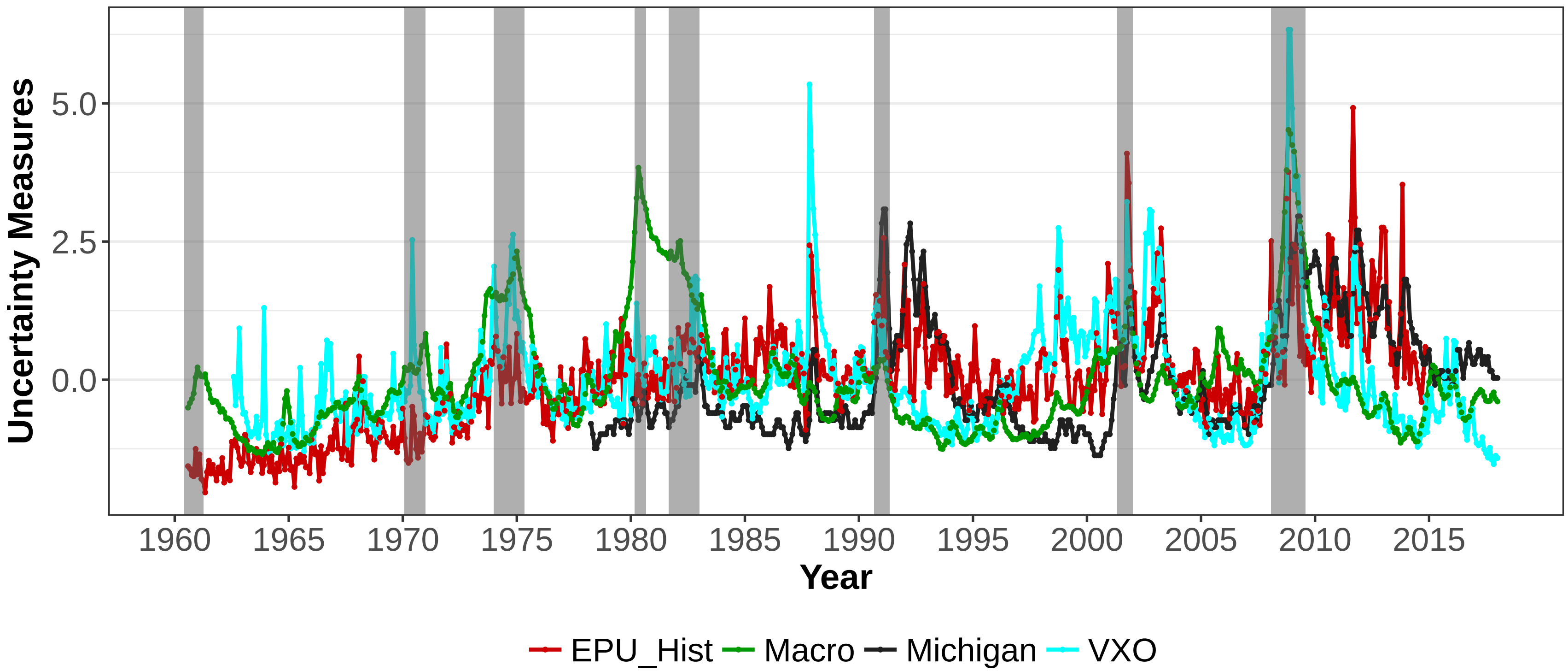

Figure 13.: Comparison of uncertainty measures (facetted). *Note:* Shaded areas denote NBER recession dates in the US. Data frequencies are monthly. The macro uncertainty series starts in July 1960, the GTU in January 2004, the EPU in January 1985, the consumer uncertainty series in January 1978 and the VXO in July 1962.

A.5. Additional VAR Results

B. Appendix

B.1. Data: Sources and Description

Table 7 lists all data and their sources that appear in the main text. Variables that enter the VAR and/or Local Projection estimations in Section 4 are listed below.

Monthly VAR-8 following Bloom (2009)

Endogenous variables, in order:
Then we create separate explanations about which variables were used for which model:

1. $\log(\text{S\&P500}_t)$
2. uncertainty (various measures)
3. FFR_t
4. $\log(\text{WAGE}_t)$
5. $\log(\text{CPI}_t)$
6. $\log(\text{HOURS}_t)$
7. $\log(\text{EMPM}_t)$
8. $\log(\text{IP}_t)$

Monthly VAR-11 following Jurado et al. (2015)

Endogenous variables, in order:
Then we create separate explanations about which variables were used for

which model:

1. $\log(\mathrm{IP}_t)$
2. $\log(\mathrm{EMPM}_t)$
3. log(real consumption –> still to be added! download from IHS!
4. $\log(\text{PCE deflator}_t)$ –> still to be added! download from IHS!
5. $\log(\mathrm{NO}_t = \text{NO capital}_t + \text{NO cons}_t)$ –> two components to be added! download from IHS!
6. $\log(\mathrm{WAGE}_t)$
7. $\log(\mathrm{HOURS}_t)$
8. FFR_t
9. $\log(\mathrm{S\&P500}_t)$
10. growth rate of $\mathrm{M2}_t$
11. uncertainty (various measures)

Local Projections (Jordà, 2005)

Table 7.: Data Sources.
Note: Federal Reserve Economic Data (FRED); Chicago Board Options Exchange (CBOE); Michigan Survey of Consumers (MSoC);

Variable	Name	Source	Code	Period
IP_t	Industrial Production Index (Monthly, Seasonally Adjusted)	FRED	INDPRO	1962M07-
$EMPM_t$	All Employees: Manufacturing (Monthly, Seasonally Adjusted)	FRED	MANEMP	1962M07-
$HOURS_t$	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Monthly, Seasonally Adjusted)	FRED	AWHMAN	1962M07-
CPI_t	Consumer Price Index for All Urban Consumers: All Items (Monthly, Seasonally Adjusted)	FRED	CPIAUSCSL	1962M07-
NO $capital_t$	Value of Manufacturers' New Orders for Capital Goods: Nondefense Capital Goods Industries (Monthly, Seasonally Adjusted)	IHS	M_178554409	1962M07-
NO $cons_t$	Value of Manufacturers' New Orders for Capital Goods: Nondefense Capital Goods Industries (Monthly, Seasonally Adjusted)	IHS	M_14385863	1962M07-
$WAGE_t$	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing (Monthly, Seasonally Adjusted)	FRED	AHEMAN	1962M07-
$M2_t$	M" Money Stock (Monthly, Seasonally Adjusted)	FRED	M2SL	1962M07-
FFR_t	Effective Federal Funds Rate	FRED	FEDFUNDS	1962M07-
$S\&P500_t$	S&P's Common Stock Price Index: Composite (Monthly)	YAHOO Finance	S&P 500 (^GSPC)	1962M07-
VXO_t	Cboe S&P 100 Volatility Index - VXO	CBOE	VXO	1986M01-
$Michigan_t$	Consumer Uncertainty (Michigan Survey of Consumers)	MSoC	veh_fb_unc	1978M03-
$Macro1/3/12_t$	Macro Uncertainty Index	Jurado et al. (2015)[1]		1962M07-
EPU_t	Economic Policy Uncertainty Index	Baker et al. (2015)[2]	News Based Policy Uncert Index	1962M07-
EPU $Historical_t$	Economic Policy Uncertainty Index	Baker et al. (2015)[3]	News-Based Historical Economic Policy Uncertainty	1962M07-

B.2. Code

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##The Code will go here.
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Declaration of Authorship

I hereby declare that I prepared this master's thesis independently and that the thoughts taken directly or indirectly from other sources are acknowledged as references accordingly.

The work contained in this thesis has neither been previously submitted to any other examination authority nor published in any other form which has led to the award of a degree.

Innsbruck, ____________________ ______________________________

(Signature: Marcel Kropp)

Eidesstattliche Erklärung

Ich erkläre hiermit an Eides Statt, dass ich dir vorliegende Masterarbeit selbständig angefertig habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher weder in gleicher noch in ähnlicher Form einer anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht.

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