Universität Innsbruck

Time-Varying Uncertainty and Business Cycles

An Inquiry into the Measurement of Uncertainty and its Macroeconomic Effects Using the Example of the US

Master's Thesis

in partial fulfillment of the requirements
for the degree of Master of Science (M.Sc.)
in Applied Economics

submitted to
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Innsbruck, July 2018

To my Mum.

What I have written five years ago 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.

But which specific events can cause (economic or political) uncertainty that ultimately feed into the micro-level giving rise to exemplary scenarios we just discussed?

On an aggregate level, as aptly formulated by Nicholas Bloom[2], after the Great Recession and the subsequent turmoil in the Eurozone's sovereign debt markets

[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.

[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.

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 intensification of tensions between forces of the West and East have brought uncertainty into the spotlight again suggesting that alleged 'tail-events' are far from improbable.

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 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 Keyne-

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

sian[4] understanding of *uncertainty*[5], its distinction from *risk* and the resulting theoretical implications[6]. 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[7].
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 dualistic interpretation was 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)[8] and fundamental uncertainty in his later

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

[5] 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.

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

[7] 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).

[8] 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).

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*[9]" (Dequech, 2011, p. 623). Dequech (2000) sees the work of Shackle (2017) as advocating this argument.

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 political, 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)[10].

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

[9] Italics added.

[10] 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).

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[11]:

1. between substantive and procedural uncertainty:[12]
2. between weak and strong uncertainty:[13]
   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 (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)[14] and de Finetti (1937));
3. between ambiguity and fundamental uncertainty.[15]

Abstracting from the (philosophical) considerations above, is there 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?

[11] Apart from this classification we do not discuss any further interrelationships between the various concepts.
[12] 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.
[13] 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).
[14] Written "in opposition" to Keynes (1921).
[15] Which are two types of strong and substantive uncertainty (Dequech, 2000).

Within the past ten years and largely triggered by a seminal work by Bloom (2009)[16], 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 '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 A including information on the data and the entire code and Appendix B including information on the differences between VARs and the local projection method by Jordà (2005).

[16] Bloom's contribution triggered a wave of studies that challenged the effects that he had reported in his initial publication in Bloom (2009).

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!

As mentioned in the Introduction above, 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.

[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.

2.1. Measuring Uncertainty

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)

[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.

- 'forecast-based'[4] - measures that rely on both an economy's predictability and the measurement of discrepancies between professional forecasts assuming that impeded predictability and a large dispersion between forecasts points at a more uncertain economy:
  * cross-sectional dispersion measures of subjective business or consumer confidence (forecasts) based on survey data: 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 2.1.5)
- '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 called 'EPU index'; see Section 2.1.3),
    in a similar vein, Moore (2016) constructs an index of economic

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

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 (henceforth called BGS-index and CT-index, respectively; see Section 2.1.4); 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. VXO/Bloom-shock: Bloom (2009)

Note to self:

- Bloom (2009) describes the identification of shocks both in the Appendix (section A.1.2, p. 675;) as well as in the main text on p. 630. The explanation in the main text states:
  "The main stock-market volatility indicator is constructed to take a value 1 for each of the shocks labelled in the figures above and a 0 otherwise. These shocks were explicitly chosen as those events *when the peak of HP detrended volatility level rose significantly above the mean.* In particular, the threshold was 1.65 standard deviations above the mean, selected as the 5% one-tailed significance level *treating each month as an independent observation.*"
- 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

The construction of the 'Bloom-shock' as outlined in Bloom (2009) is performed in multiple steps and uses two data-sources[6]: (i) VXO-data from the Chicago Board Options Exchange (CBOE) for the period where data is available (i.e., 1986 - 2018)[7] and (ii) actual monthly volatilities (for the period pre-1986) calculated as the monthly standard deviation of the daily S&P500 index (normalized to the same mean and variance as the VXO index for when the two

[6]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.

[7]The VXO - index (for details see the the homepage of the CBOE) reflects the market's expected implied volatility based on S&P100 options 30 days to expiration and hence captures expected volatility of equity prices. Note that the VIX introduced as of 2003 instead is based on prices of S&P500 options.

series overlap, i.e., from 1986 - 2003)[8]. The result is one continuous volatility measure as shown in Figure 1.[9]

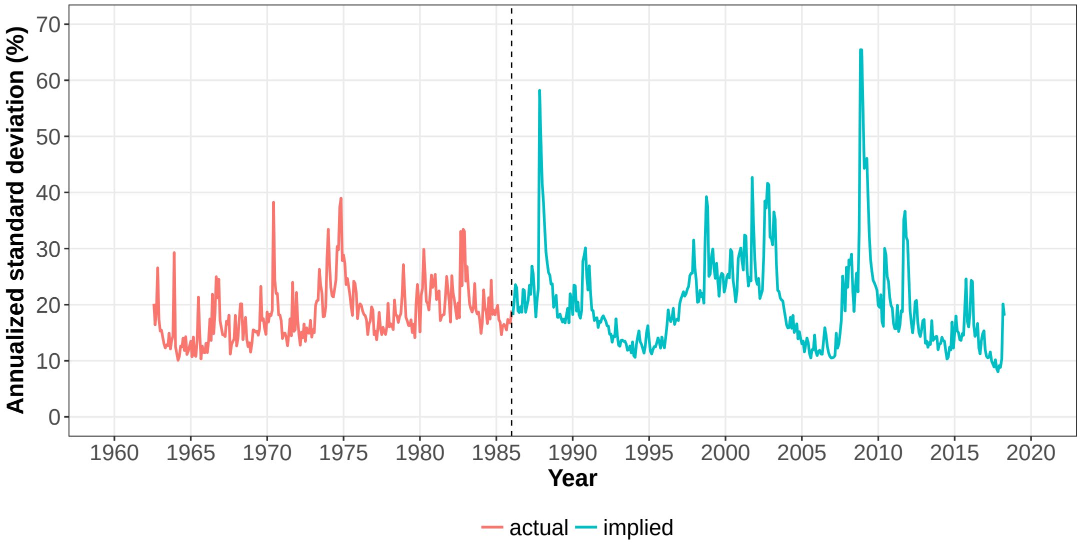

Figure 1.: Monthly U.S. stock market volatility. *Note:* From 1986 onwards CBOE VXO index of percentage implied volatility, on a hypothetical at the money S&P100 option 30 days to expiration. Before 1986 actual monthly returns volatilities are calculated as the monthly standard deviation of the daily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

The derivation of the 'Bloom-shocks' (i.e., an indicator variable that takes a value of 1 for an event labelled as a 'shock') then works as follows:

i detrend the volatility-measure from above (Bloom (2009) uses a HP-filter with $\lambda = 129,600$);

ii according to Bloom (2009), the actual 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 stock-market volatility series; thereby each month is being treated as an independent observation

Ultimately, this results in identified 'shocks' as shown in Figure 2 where the

[8] The R-Code replicating all the steps for the construction of the Bloom-shock is available in Appendix A.2.

[9] In the following we refer to this spliced version as the VXO index.

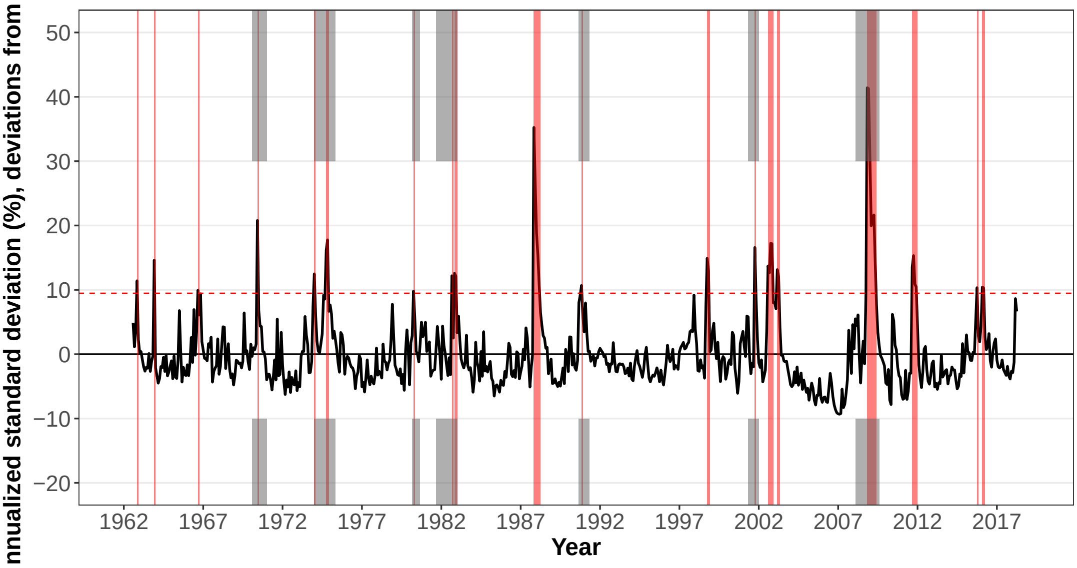

Figure 2.: Monthly U.S. stock market volatility. Red shaded areas correspond to dates where volatility series exceeds 1.65 standard deviation above the series' mean. Grey shaded areas denote NBER recession dates in the US.

shaded areas correspond to the 'Bloom-shock' being equal to 1 (i.e., where the dashed horizontal line representing 1.65 standard deviations above the HP filtered mean crosses the detrended series). Accordingy, Table 1 spells out the exact dates of the identified shocks including when the 'Bloom-shock' started (first column), when it ended (second column), the amount of consecutive months within a dedicated shock-period (third column), the date with the maximum volatility within the dedicated shock-period (fourth column) and the corresponding maximum volatility in the last column.

2.1.2. Michigan Survey: Leduc and Liu (2016)

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

Table 1.: Replication of shocks following Bloom (2009).

yearmon_start	yearmon_end	duration	yearmon_max	max_vol
Nov 1962	Nov 1962	1 months	Nov 1962	26.58%
Dec 1963	Dec 1963	1 months	Dec 1963	29.28%
Sep 1966	Sep 1966	1 months	Sep 1966	24.99%
Jun 1970	Jun 1970	1 months	Jun 1970	38.27%
Jan 1974	Jan 1974	1 months	Jan 1974	33.44%
Oct 1974	Nov 1974	1 months	Nov 1974	38.98%
Apr 1980	Apr 1980	1 months	Apr 1980	29.86%
Sep 1982	Sep 1982	1 months	Sep 1982	33.05%
Nov 1982	Dec 1982	2 months	Nov 1982	33.43%
Nov 1987	Mar 1988	5 months	Nov 1987	58.22%
Nov 1990	Nov 1990	1 months	Nov 1990	30.13%
Oct 1998	Nov 1998	1 months	Oct 1998	39.25%
Oct 2001	Oct 2001	1 months	Oct 2001	42.69%
Aug 2002	Nov 2002	4 months	Oct 2002	41.66%
Mar 2003	Apr 2003	1 months	Mar 2003	36.54%
Nov 2008	May 2009	7 months	Nov 2008	65.45%
Sep 2011	Dec 2011	4 months	Oct 2011	36.64%
Oct 2015	Oct 2015	1 months	Oct 2015	24.60%
Feb 2016	Mar 2016	2 months	Feb 2016	24.33%

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]

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*

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

[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.

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 3.

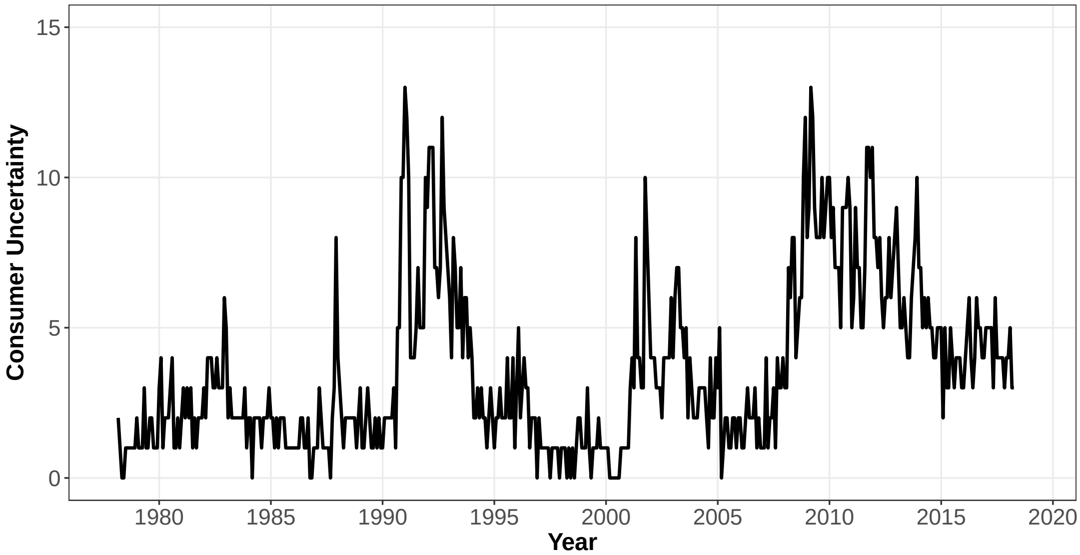

Figure 3.: Thomson Reuters/University of Michigan Survey of Consumers, Consumer Uncertainty.

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. Economic Policy Uncertainty Index: Baker et al. (2015)

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!

- **?**, p. 1593 write: "We develop a new index of economic policy uncertainty (EPU) based on newspaper coverage frequency. Several types of evidence - including human readings of 12,000 newspaper articles - indicate that our index proxies for movements in policy-related economic uncertainty. Our U.S. index 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."

- **?**, 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."

- **?**, p. 1593 write: "Extending our U.S. index back to 1900, EPU rose dramatically in the 1930s (from late 1931) and has drifted upward since the 1960s." –> This is a sentence that we should include in our description of the time-series itself!

2.1.4. [Google Trends-based Index: Bontempi et al. (2016) and Castelnuovo and Tran (2017)]

Google Trends is a freely available Google service derived from Google search data. As such it is a powerful tool when it comes to the exploration of global

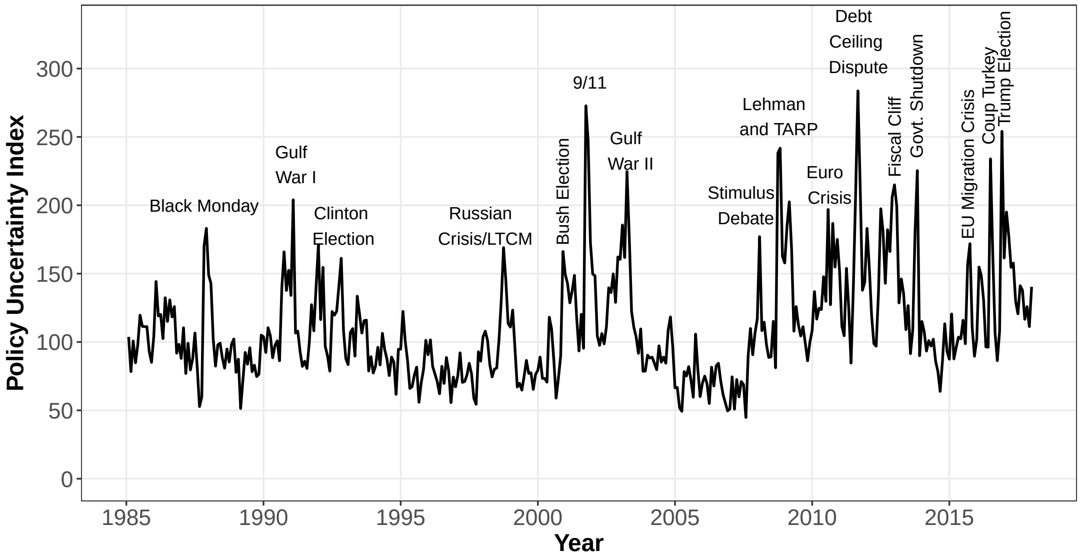

Figure 4.: EPU Index for the United States. *Note:* Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy, and one or more policy relevant terms: 'regulation', 'federal reserve', 'deficit', 'congress', 'legislation', or 'white house'. The series is normalized to mean 100 from 1985-2009 and based on queries run on 2 February, 2015 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. Original Figure Iå in Baker et al. (2015) spans until 2015. We have taken all available values until April 2018, inclusive.

reactions to major events based on what people search for world-wide.[12] The data that Google makes available thereby can be filtered in two ways: (i) **real time**, which is a random sample of searches from the last seven days and (ii) **non-real time** which is a random sample of the full Google dataset which can go back anywhere from 2004 to ca. 36 hours ago.[13]

The feature that actually makes Google Trends useful is that it is normalized, meaning that when looking at the search interest for a specific topic over time, the presented data points show *the proportion of all searches on all topics on Google at that particular time and location.* Only this makes the search interest for a particular topic across time (and potentially additionally across

[12]For more information see https://support.google.com/trends/?hl=en#topic=6248052.

[13]The algorithm reverts to sampling because otherwise the query to trillions of Google searches could not be executed within a reasonable amount of time.

locations) comparable in the first place. The reported numbers are indexed to 100 (with 100 standing for the maximum search interest for a particular time and location selected).

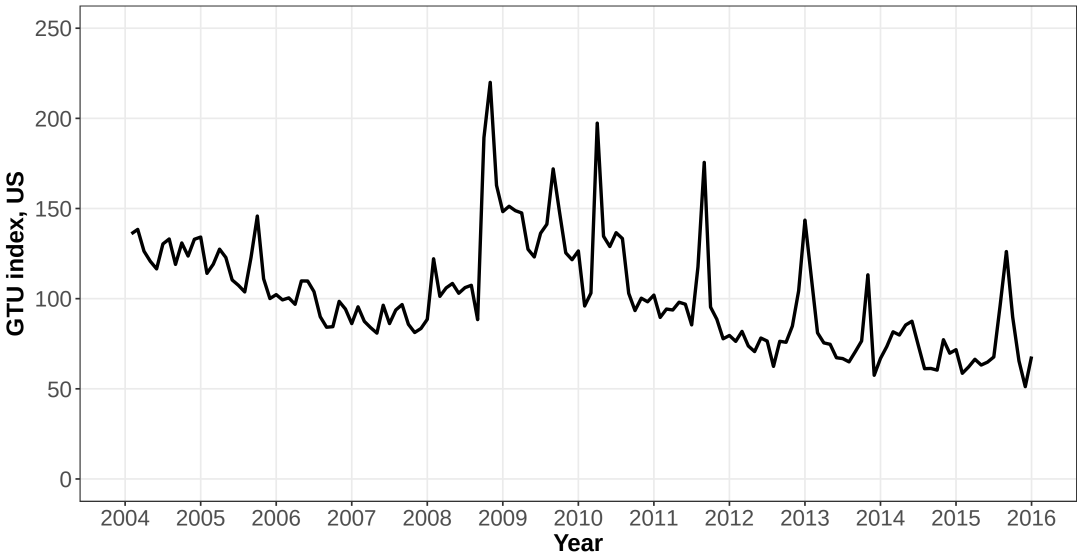

Figure 5.: Google Trends Uncertainty (GTU) index. *Note:* Sample: 2004M1-2016M12. Index constructed by weighting search queries related to a battery of country-specific keywords as explained above and normalized to have mean = 100 and standard deviation = 30.

Bontempi et al. (2016, p. 3) summarize the rationale to use Internet searches, stating that "[h]igher levels of uncertainty are likely to result in a greater appetite for knowledge, and consequently in a more intense use of tools capable of gathering further information." Hence, the linkage between uncertainty about the outcome of a specific political or economic event and the potential resulting intensity of Internet searches which is assumed to mirror individuals' perceived uncertainty is exploited.

Castelnuovo and Tran (2017) construct Google Trends-based uncertainty indices (henceforth called GTU indices) for the United States and Australia.[14] Their index is based on frequently mentioned keywords appearing in reference

[14]In the following we will only consider the case of the US and therefore also continue to speak of only one GTU *index*.

economic documents like the Federal Reserve's Beige Book[15] (for the United States) in connection to the word *uncertainty*. The authors report to have subjectively selected relevant search-terms from various editions of the Beige Book resulting in 79 keywords for the U.S. (the complete list is available in the appendix of Castelnuovo and Tran, 2017).

The aggregation based on the 79 identified keywords is then performed as follows (see Castelnuovo and Tran (2017)):
As already indicated above, Google Trends data reports the frequency of a particular search term relative to the total search volume $S_{i,j,m,c}$ by dividing each raw data point $R_{i,j,m,c}$ (the frequency of a word i in a group of searched words j in period m in location c) by the total searches T in the same period/location so that $S_{i,j,m,c} = \frac{R_{i,j,m,c}}{T_{m,c}}$.

2.1.5. Macro Uncertainty Index: 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.[16]

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."

[15]The Beige Book gathers anecdotal information on current economic conditions based on interview with, among others, key business contacts, economists and market experts. See https://www.federalreserve.gov/monetarypolicy/beige-book-default.htm for more information.

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

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 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 measure of time-varying uncertainty is 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

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, followed by the 1981-1982 recession as a close second).[17][18]

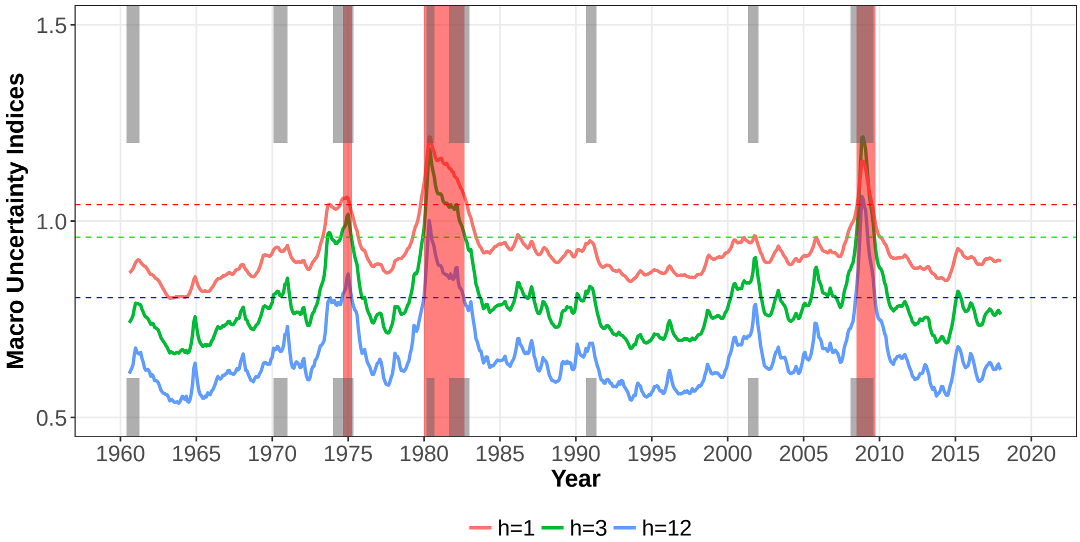

Figure 6.: Aggregate Uncertainty: $h = 1, 3, 12$. *Note:* Horizontal lines indicate 1.65 standard deviations above the mean of each series. Data are monthly and span the period 1960:7-2017:12. Red shaded areas correspond to dates where volatility series exceeds 1.65 standard deviation above the mean 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 uncertainty-measure developed by Jurado et al (which is very complicated!)

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

[18] 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.

2.1.6. 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`

2.1.7. A 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))
- 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,[19], 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

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

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:

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

where $I_{A_k,t}$ is the information of agent k at time t, and w^A_k is the weight applied to agent k. One potential advantage of using $D^A_{jt}(h)$ 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. Comparison of Selected Measures

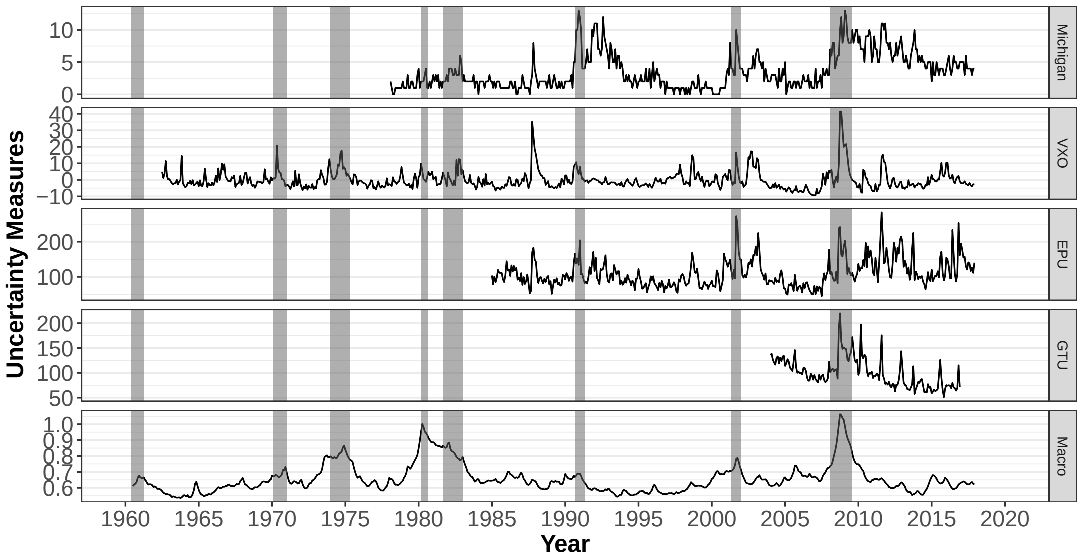

Figure 7.: Comparison of uncertainty measures (facetted). *Note:* Shaded areas denote NBER recession dates in the US. Data frequencies are monthly. The macro uncertainty series starts in July 1960, the GTU in January 2004, the EPU in January 1985, the consumer uncertainty series (Michigan Survey) in February 1978 and the VXO/stock-market volatility series in July 1962. Note to self: We define high uncertainty events as months when either uncertainty measure was one standard deviation above its time series average. (still have to add these values to the plots!))

Figures 7 (on different scales) and 8 (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 inspection shows 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 show much noisier fluctuations than e.g., the macro uncertainty index. And while the VXO and EPU show a similar trajectory prior to the crisis, the EPU remains elevated during most of the recovery period showing more variation including several spikes (comparable to the GTU over that period). At a first glance, this suggests that the EPU indeed reacts much stronger to the political turmoil in the past decade than financial markets themselves.

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[20] 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 at Figures 7 and 8 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 on '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).

[20]Italics added.

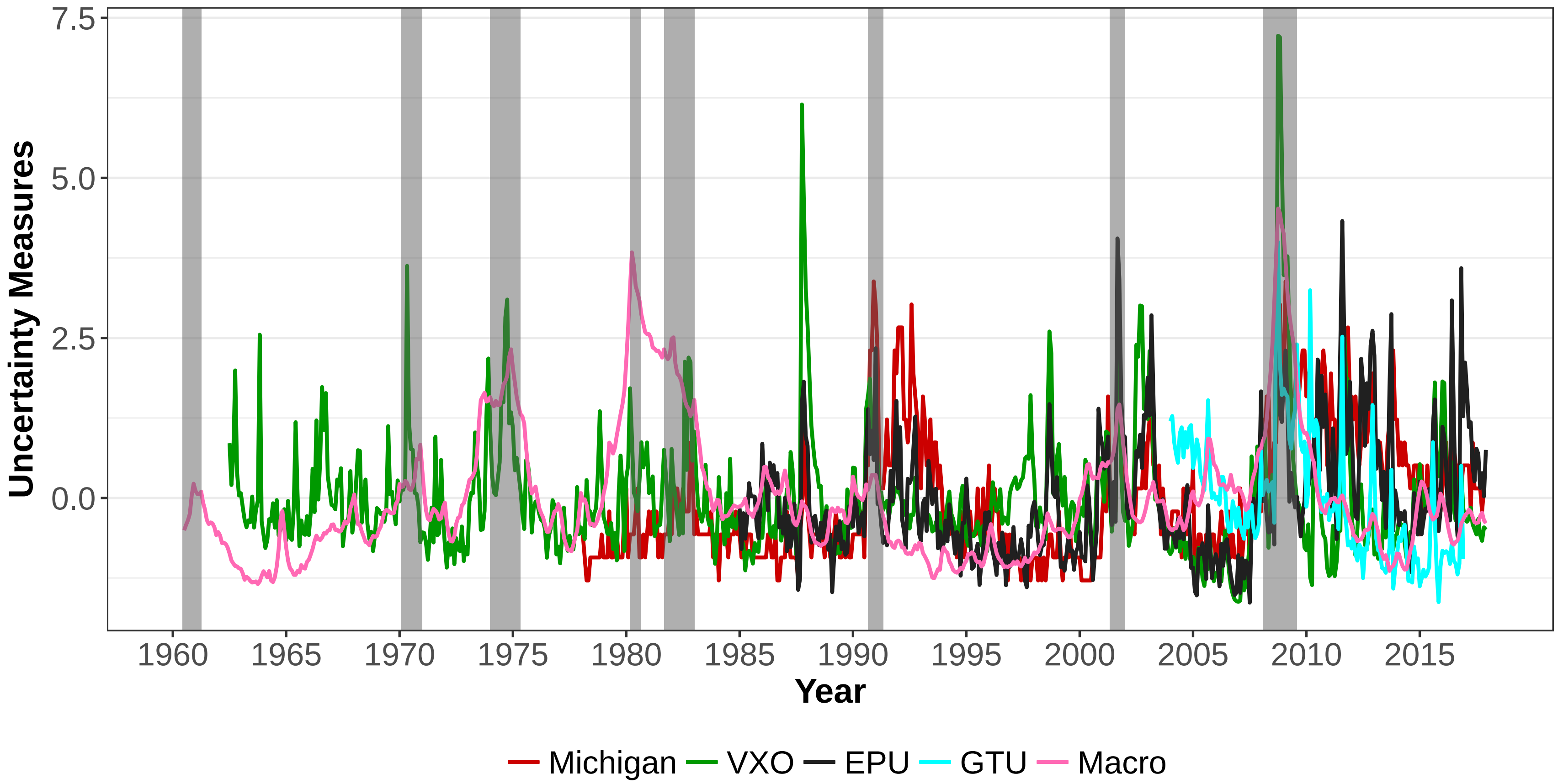

Figure 8.: Comparison of uncertainty measures (facetted). *Note:* Shaded areas denote NBER recession dates in the US. Data frequencies are monthly. The macro uncertainty series starts in July 1960, the GTU in January 2004, the EPU in January 1985, the consumer uncertainty series in January 1978 and the VXO in July 1962.

Table 3.: Correlation matrix of uncertainty measures.

	MSoC	VXO	EPU	GTU	Macro
MSoC	1	0.510	0.600	0.240	0.340
VXO	0.510	1	0.530	0.360	0.630
EPU	0.600	0.530	1	0.250	0.150
GTU	0.240	0.360	0.250	1	0.620
Macro	0.340	0.630	0.150	0.620	1

And while there is an overall comovement 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 prove the above statement, we will study the time-series properties of the various uncertainty measures in turn (results will be plotted below!).

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!

- add a table with the cross-correlation between the various measures!

- Jurado et al. (2015) provide a table with summary statistics of their uncertainty measures for $h = 1$. Their table reports the first-order autocorrelation coefficient, estimates of the half-life of an aggregate uncertainty innovation from a univariate autoregression (AR) for U_t(1), estimates of skewness, and kurtosis, and IP-Corr(k) is the (absolute) cross-correlation of Ut with industrial production growth at different leads and lags, k. The same statistics are reported for other uncertainty proxies,. Several statistical facts about their own estimate of aggregate uncertainty stands out in Table 1.
  Of course, these unconditional correlations are uninformative about the causal relation between uncertainty and real activity. All that can be said is that there is a strong coherence between uncertainty and real activity.

- Similar to Jurado et al. (2015) I should add a table with summary statistics of the various volatility series (including their half-life, etc.)

- 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)).'

- Jurado et al. (2015, p. 1180) write: "Moreover, our estimate of macroeconomic uncertainty is far more persistent than stock market volatility: the response of macro uncertainty to its own innovation from an autoregression has a half-life of 53 months; the comparable figure for stock market volatility if four months.
- 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 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. Some Stylized Facts

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?

3. Related Literature

The literature that investigates the linkages of uncertainty on various macroeconomic aggregates (and beyond) is extensive including both empirical and theoretical work. An often-cited theoretical study which is seen as a pioneering work in the field of uncertainty-studies is Bernanke (1983) who 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. Subsequent selected works include, 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.[1]

The growing body literature that has recently started to systematically study economic uncertainty in an attempt to understand its origins and the *potential* causal effects of time-varying economic uncertainty on macroeconomic fluctuations (business cycles) 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 have pointed to somewhat heterogeneous output responses."

[1]Note that the list of studies is not supposed to be exhaustive.

The study whose results serve as a benchmark for our own analysis by replicating parts of it 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 with 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 then 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 of the controversy in the literature. In particular, using 17 identified exogenous shocks, Bloom (2009) estimates VARs showing that volatility shocks generate a short-run drop in industrial production of 1% which last for about 6 months 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).

Contrary to Bloom's findings when using stock market volatility as a proxy for uncertainty, Jurado et al. (2015) and Bachmann et al. (2013) using forecast-based measures 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).

While Bloom (2009) sees a confirmation for the 'wait-and-see approach' (Maybe I should add here a sentence starting with 'Central to Bloom's argumentation is the 'wait-and-see approach' and then explain the intuition behind it as outlined in Bachmann et al. (2013)) according to his results, whereas Bachmann et al. (2013), using survey data get contrary predictions:
citetbachmannetal:13 write on p. 28: “This is at least suggestive evidence that uncertainty is a concomitant factor of bad economic times rather than a causal factor for them.”

Here I then should summarize the papers that refer to Bloom's paper and everything related to papers that study the effect of uncertainty on business cycles. Here I should mention that uncertainty is an ubiqitous concern of policymakers (and quote a few examples that also Bloom refers to both in Bloom (2009) and his presentation slides that are based on Bloom (2012)).

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).

Jurado et al. (2015) write on p. 1182: "Bloom's VAR estimates suggest that uncertainty has an impact on output and employment in the six months after an innovation in these measures, with a rise in volatility at first depressing real activity and then increasing it, leading to an over-shoot of its long-run level, consistent with the predictions of models with uncertainty as a driving force of macroeconomic fluctuations. Bloom et al. (2012) also documented a relation between real activity and uncertainty as proxied by dispersion in firm-level earnings, industry-level earnings, total factor productivity, and the predictions of forecasters. A recurring feature of these studies is that the uncertainty proxies are strongly countercyclical."

Orlik and Veldkamp (2014) write

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 permanent?
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?

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

4. Empirical Analysis

Note to self:

- 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 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

[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.

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 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.

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,

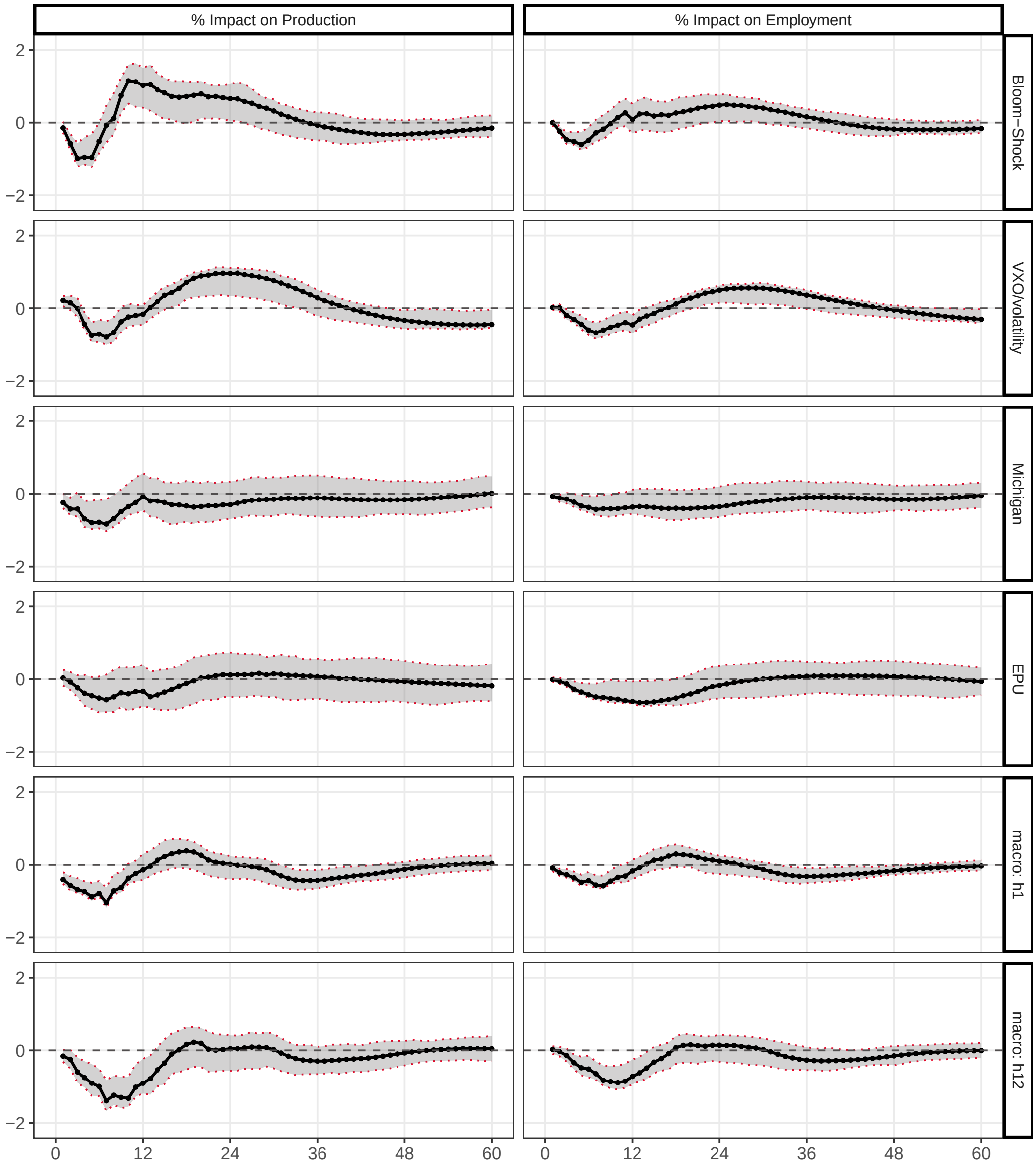

Figure 9.: Impulse Response Functions of Production and Employment from Estimations of VAR-8 following Bloom (2009) using all uncertainty measures. Variables enter the VAR-8 according to 4.1.
Note: Dashed lines show 68% standard error bands. The data are monthly and span the period 1962:07-2008:06 for 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 $h = 12$).

replicated from the model in Bloom (2009).

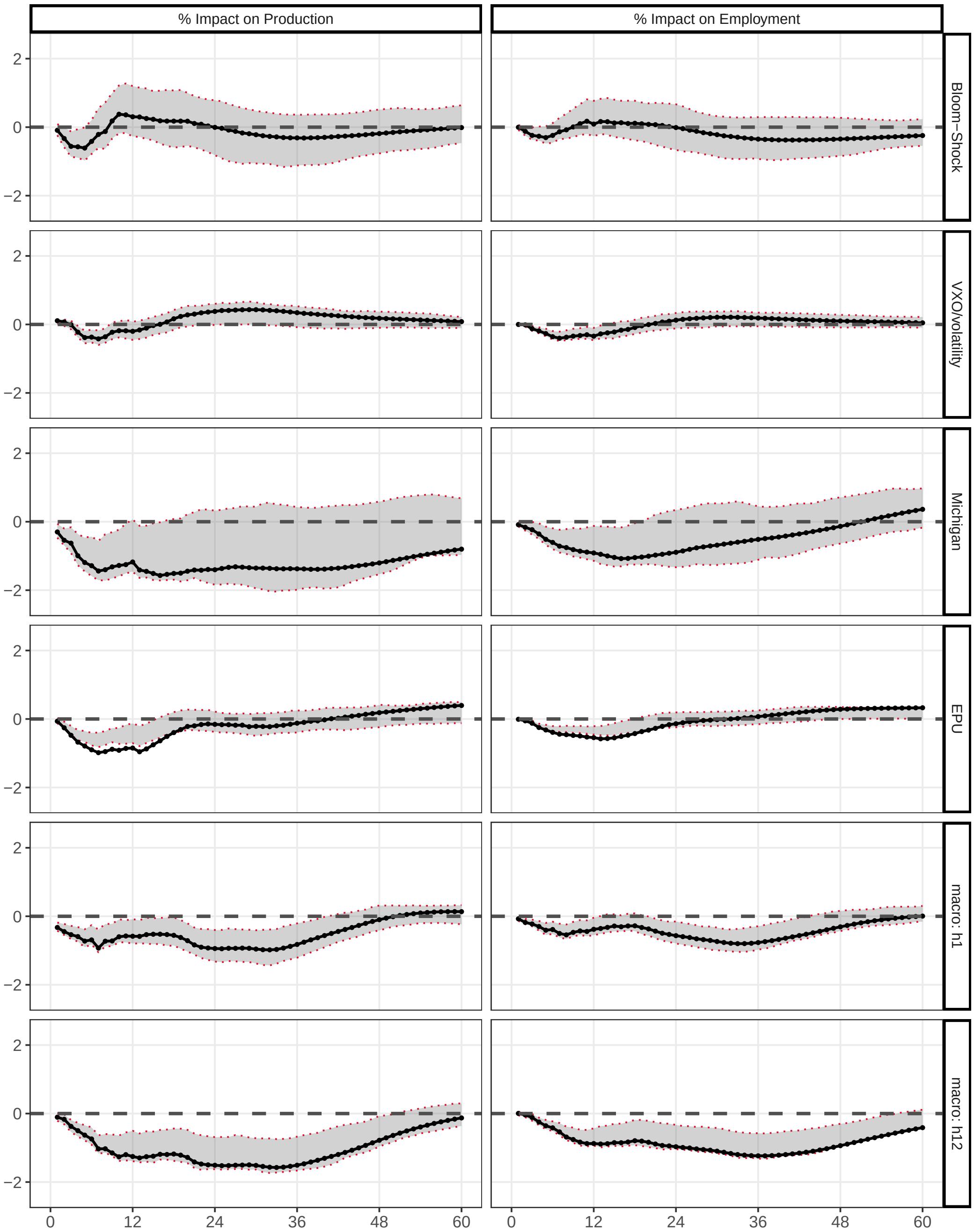

Figure 10.: Impulse Response Functions of Production and Employment from Estimations of a modified version of the VAR-8 Bloom (2009) using all uncertainty measures. Variables enter the VAR-8 according to 4.1.
Note: Dashed lines show 68% standard error bands. The data are monthly and span the period 1962:07-2008:06 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 $h = 12$).

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 A.1

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)."

[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.

- 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?

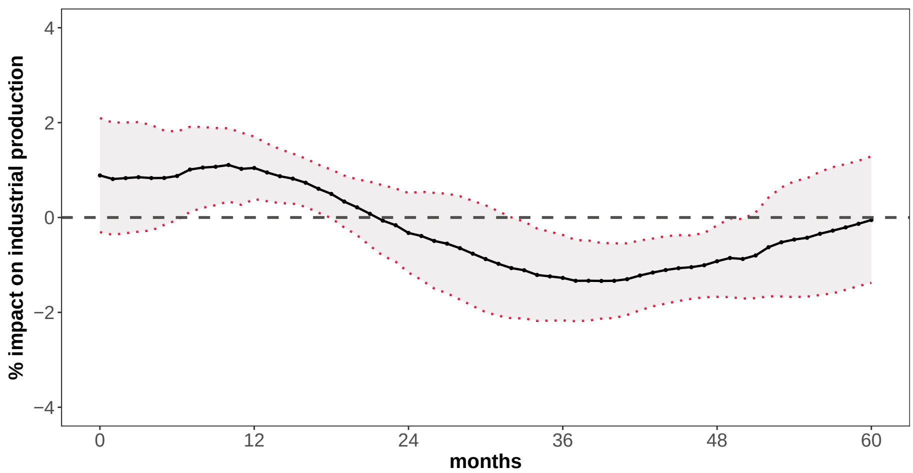

Figure 11.: Local projection estimations of the impact of a volatility shock on industrial production. *Note:* Dashed lines are 1 standard-error bands around the response to a volatility shock.

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

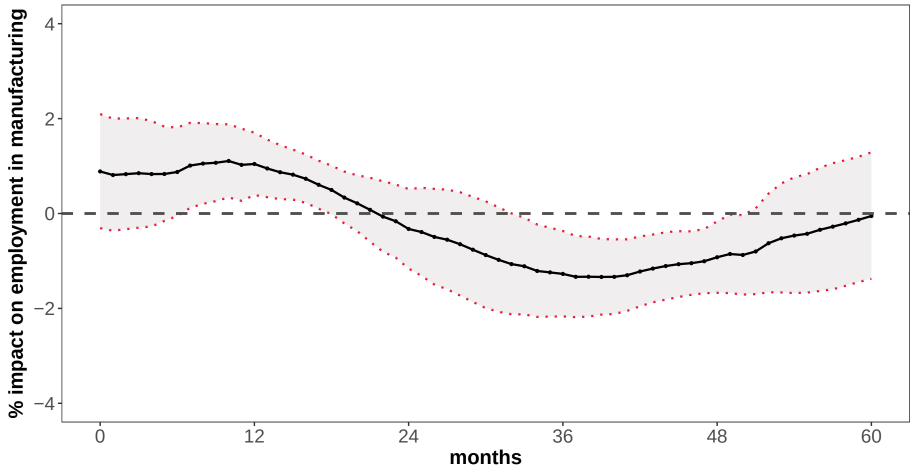

Figure 12.: Local projection estimations of the impact of a volatility shock on industrial production. *Note:* Dashed lines are 1 standard-error bands around the response to a volatility shock.

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.

5. Conclusion

A. Appendix

A.1. Data: Sources and Description

Table with all the series used (using an internal numbering)

No. Short Name Source Code Tran Description 1 IP: mfg IHS Global Insights M_116461013 deltaln Industrial Production Index - Manufacturing IP_MAN: Industrial Production: Manufacturing (NAICS) (Board of Governors) Obtained via FRED (series name: IPMAN)

(note: I have, for now, downloaded the data from FRED; therefore my numbers are slightly different!) 2 Emp: mfg IHS Global Insights M_123109542 deltaln Employees on Nonfarm PAyrolls: manufacturing EMP_MAN: AAll Employees: Manufacturing, SA (BLS) Obtained via FRED (series name: MANEMP)

3 Avg hrs: mfg IHS Global Insights M_14386098 deltaln Average Weekly Hours of Production and Nonsupervisory Workers: manufacturing HOURS_MAN: Average Weekly Hours of Production and Nonsupervisory Emploees: Manufacturing, SA (BLS) Obtained via FRED (series name: AWHMAN)

4 CPI-U: all IHS Global Insights M_110157323 delta^2 ln CPI-U: all items CPI: Consumer Price Index for All Urban Consumers: All Items (BLS) Obtained via FRED (series name: CPIAUSCL)

5 AHE: mfg IHS Global Insights M_123109552 delta^2 ln Avg Hourly Earnings of PRod or Nonsup Workers Private Nonfarm - Manufacturing EARN_MAN: Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing, SA (BLS) Obtained via FRED (series name: AHEMAN)

6 Fed Funds IHS Global Insights M_110155157 deltalv Interest Rate: Federal Funds FEDFUNDS: Loga Effective Federal Funds Rate, NSA (Boar dof Governors) Obtained via FRED (series name: FEDFUNDS)

7 S&P 500 IHS Global Insights M_110155044 deltaln S&P's Common Stock Price Index: Composite

Then we create separate explanations about which variables were used for which model:

for VAR-8 estimations (following Bloom (2009) Industrial Production Index (IP): manufacturing –> Source: IHS Global Insights

for VAR-11 estimations (following Bloom (2009)

A.2. Code

```
##The Code will go here.
```

B. Appendix

B.1. IRFs in a VAR-Setting

B.2. IRFs and Local Projections

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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)