Universität Innsbruck

Uncertainty and Business Cycles

An Empirical Analysis using Local Projections (work in progress)

Masterarbeit

zur Erlangung des akademischen Grades eines
Master of Science (M.Sc.)
in Applied Economics

eingereicht bei Herrn
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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

Similarly to how Bloom (2009) has mentioned that studying uncertainty is incredibly topical given the recent Brexit and Trump election outcomes (see `https://site.stanford.edu/2018/session-6`), I could start the introduction along similar lines.[1].

Some notes to myself when reading through some of the articles:

- "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

[1]The mentioned link is about a Summer Workshop related to 'Macroeconomics of Uncertainty and Volatility' in which Bloom also briefly mentions that the theoretical and empirical understanding of how uncertainty affects economies as a whole is still limited since macroeconomists only recently have started working on these issues from a more systematic basis. Still, he mentions about 14 recent papers on this topic (which are not yet posted online but which I could include into the literature review as well!)

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 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.

1.1 A Historical View on Uncertainty

1.2 Characteristics of Uncertainty Shocks

1.3 Measuring Uncertainty

1.3.1 Bloom-Shock

- 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*."

Because stock markets quickly reflect any arrival of new information, the *volatility* thereof can serve as a proxy for uncertainty.
The construction of the 'Bloom-shock' following Bloom (2009) is performed in multiple steps[2] and uses two data-sources: (i) VXO-data from the CBOE for the period where data is available (i.e., 1986 - 2018) 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 series overlap, i.e., from 1986 - 2003). The result of the manipulations is one continuous volatility measure that Bloom (2009) uses as the basis of the shocks that he considers as shown in Figure 1.

The derivation of the 'Bloom-shocks' (i.e., an indicator variable that takes

[2]The complete R-Code replicating all the steps is available in Appendix A.2.

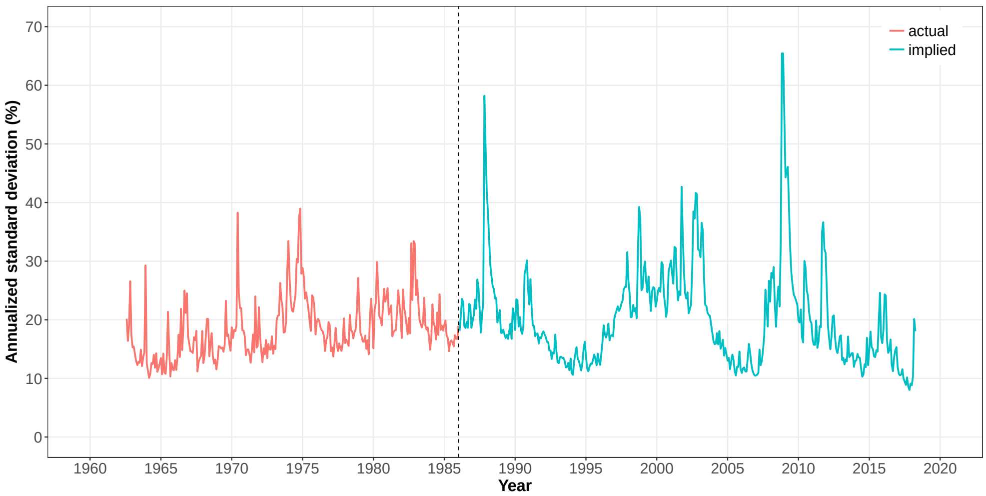

Figure 1: Monthly U.S. stock market volatility. *Note:* From 1986 onwards CBOE VXO index of percentage implied volatility, on a hypothetical at the money S&P100 option 30 days to expiration. Before 1986 actual monthly returns volatilities are calculated as the monthly standard deviation of the daily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

a value of 1 for an event labelled as a 'shock') then is done as follows:

i detrend the volatility-measure from above (Bloom (2009) uses a HP-filter with $\lambda = 129,600$); see also Figure 2 below which shows the calculated *trend*-series in red.

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 (see Figure 3; dates where the dashed line crosses the volatility-series are considered shocks)

Ultimately, this results in identified 'shocks' as shown in Figure 4 which is a replication of Figure 2 but with the episodes added that correspond to the 'Bloom-shock' being equal to 1. Correspondingly, Table 1 spells out the exact dates.

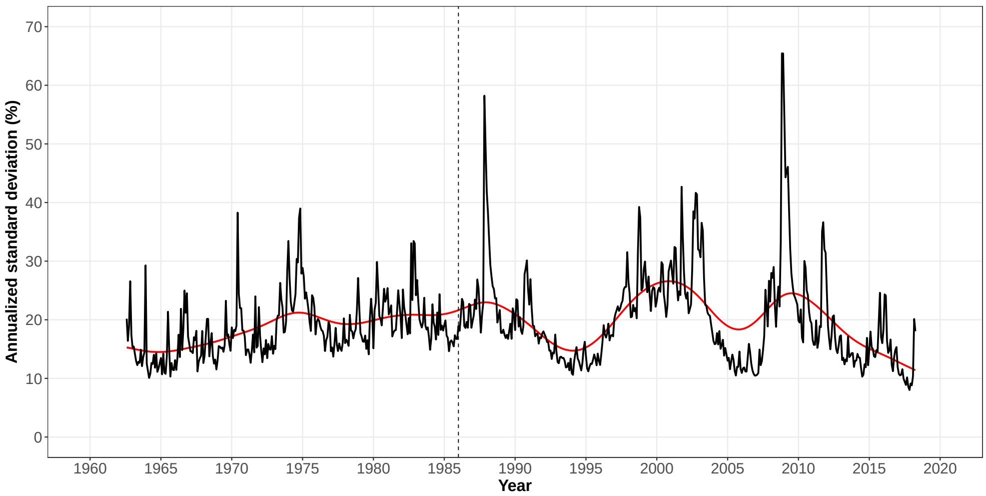

Figure 2: Monthly U.S. stock market volatility and HP-filtered trend. *Note:* HP-filtered trend was calculated using a smoothing parameter $\lambda = 129,6000$.

1.3.2 Alternative Uncertainty-Measures

- I could potentially at some point refer to economic sentiment indicators like `https://www.oenb.at/en/Statistics/Standardized-Tables/\Economic-and-Industry-Indicators/Economic-Indicators/Economic-Sentiment-` `html` or `https://data.europa.eu/euodp/data/dataset/c04BuUz6WXIQGJkHPwLug`.

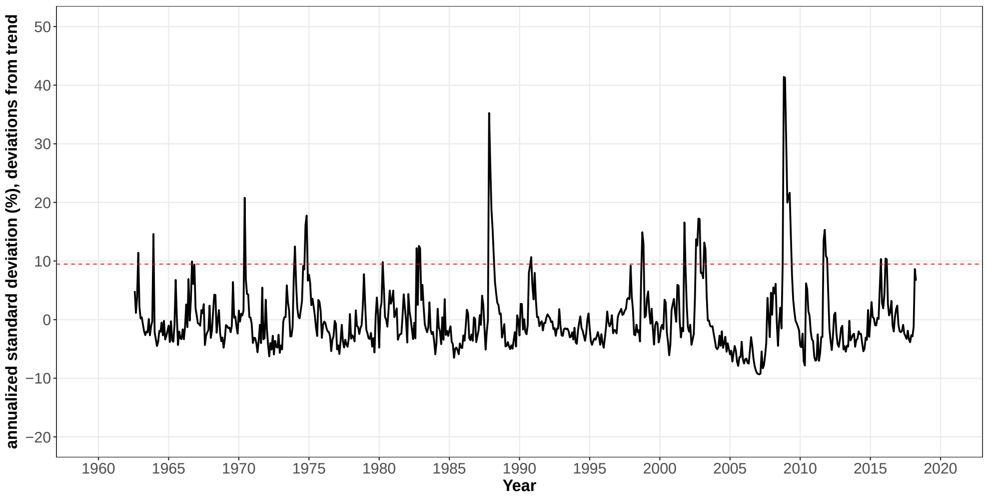

Figure 3: Monthly U.S. stock market volatility and HP-filtered trend. *Note:* HP-filtered trend was calculated using a smoothing parameter $\lambda = 129,6000$.

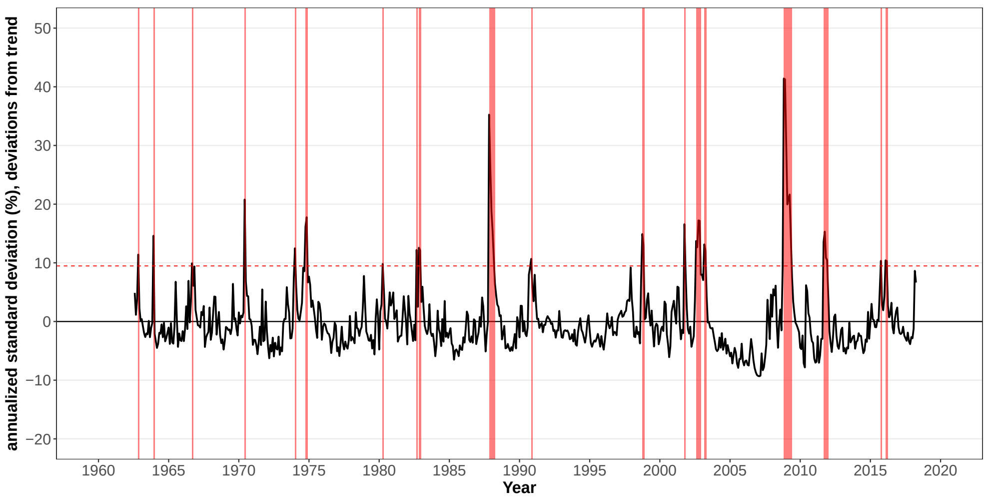

Figure 4: Monthly U.S. stock market volatility including Bloom-shocks (shaded areas).

Table 1: Replication of shocks using Bloom's methodology.

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%

2. Methodology

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:[1]

$$z_{t+h} = \alpha_h + \theta_h shock_t + controlvariables + \epsilon_{t+h} \tag{2.1}$$

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

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

above.[2] 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

[2] All variables are HP-detrended.

3. Results

Figures 5 and 6 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)
- 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?

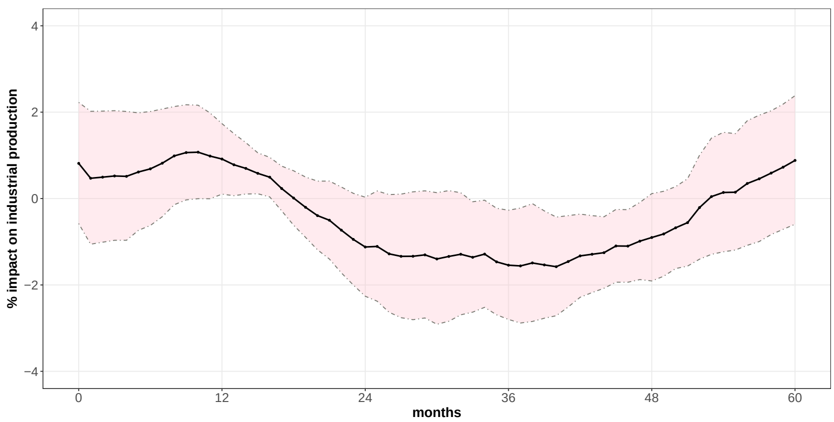

Figure 5: Local projection estimations of the impact of a volatility shock on industrial production. *Note:* Dashed lines are 1 standard-error bands around the response to a volatility shock.

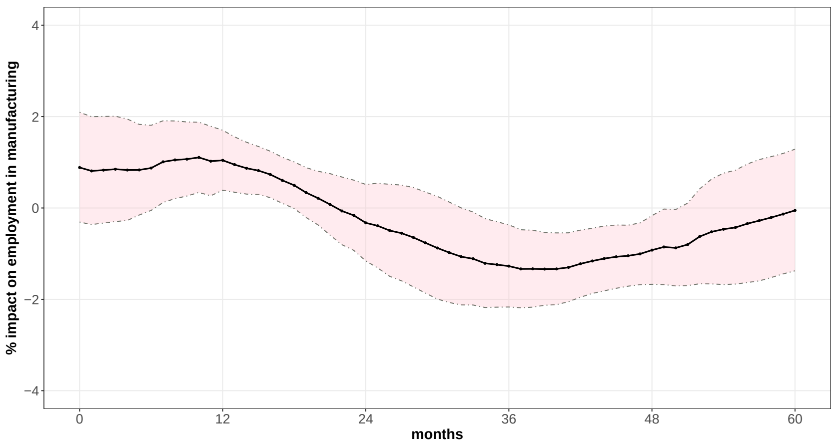

Figure 6: Local projection estimations of the impact of a volatility shock on industrial production. *Note:* Dashed lines are 1 standard-error bands around the response to a volatility shock.

4. Conclusion

A. Appendix

A.1 Data

A.2 Code

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

B. Appendix

B.1 IRFs in a VAR-Setting

B.2 IRFs and Local Projections

Bibliography

Bloom, N. (2009), 'The Impact of Uncertainty Shocks', *Econometrica* **77**(3), 623–685.

Jordà, Ò. (2005), 'Estimation and inference of impulse responses by local projections', *American Economic Review* **95**(1), 161–182.

Newey, W. and West, K. (1987), 'A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix', *Econometrica* **55**(3), 703–08.

Ramey, V. A. (2016), Macroeconomic Shocks and Their Propagation, NBER Working Papers 21978, National Bureau of Economic Research, Inc.

Ramey, V. A. and Zubairy, S. (2018), 'Government spending multipliers in good times and in bad: Evidence from us historical data', *Journal of Political Economy* **126**(2), 850–901.

Romer, C. D. and Romer, D. H. (2017), 'New evidence on the aftermath of financial crises in advanced countries', *American Economic Review* **107**(10), 3072–3118.

Eidesstattliche Erklärung

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

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

Innsbruck, July 2018

(Marcel Kropp)