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In light of the recent discussion regarding the measurement of uncertainty and its impact on economic activity, this paper derives forward-looking measures of uncertainty and directional expectations for the CHF/EUR exchange rate based on over-the-counter option data and analyses its impact on exports. First, risk-neutral option-implied probability density functions are estimated and corrected for risk aversion. Second, the standard deviations of the densities are purged from uncertainty spillovers from the Eurozone. The resulting time series serves as a forward-looking measure of exchange rate uncertainty, while the densities' skewness serves as a measure of directional expectations. Within a nonlinear threshold VAR framework, it is found that the exchange rate uncertainty measure defines a high uncertainty regime during recessions and market turmoil, and a low uncertainty regime during expansionary phases. Nonlinear impulse response analysis demonstrates that shocks to the exchange rate, the uncertainty and the directional expectations exhibit different dynamic impacts on exports during times of high and low uncertainty.

JEL classifications: C58, D84, E44, F31

Keywords: Swiss franc/Euro exchange rate, uncertainty shock, option-implied PDF, threshold VAR

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The Impact of CHF/EUR Exchange Rate Uncertainty on Swiss Exports to the Eurozone: Evidence from a Threshold VAR*

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February 14, 2019

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In light of the recent discussion regarding the measurement of uncertainty and its impact on economic activity, this paper derives forward-looking measures of uncertainty and directional expectations for the CHF/EUR exchange rate based on over-the-counter option dataand analyses its impact on exports. First, risk-neutral option-implied probability density functions are estimated and corrected for risk aversion. Second, the standard deviations of the densities are purged from uncertainty spillovers from the Eurozone. The resulting time series serves as a forward-looking measure of exchange rate uncertainty, while the densities' skewness serves as a measure of directional expectations. Within a nonlinear threshold VAR framework, it is found that the exchange rate uncertainty measure defines a high uncertainty regime during recessions and market turmoil, and a low uncertainty regime during expansionary phases. Nonlinear impulse response analysis demonstrates that shocks to the exchange rate, the uncertainty and the directional expectations exhibit different dynamic impacts on exports during times of high and low uncertainty.

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1 Introduction

Recent evidence suggests that uncertainty is an additional driver of the business cycle. Since the seminal paper by Bloom (2009), a vast amount of research has been conducted, analysing the impact of different types of uncertainty on macroeconomic aggregates. The major finding is that uncertainty moves countercyclically and depresses real activity.

Building upon this research, this paper demonstrates empirically the impact of nominal exchange rate uncertainty as a potential driver of the business cycle in small open economies, which are dependent upon international trade. Switzerland is a suitable example of a trade-dependent economy as it generates a momentous part of its GDP through exports and has a significant fraction of its trade with countries within the Eurozone.[1] Therefore, the CHF/EUR exchange rate is of major importance to the Swiss economy. Although exports are affected by the real exchange rate, research conducted by Ganguly and Breuer (2010) and Liang (1998) demonstrates that the main driver of real exchange rate volatility in developed economies is the nominal exchange rate volatility. As the export revenue measured in the domestic currency fluctuates along with the exchange rate, corresponding uncertainty and expectations regarding the direction of its future movement might affect firms' decision to expand or contract international business. Therefore, uncertainty and directional expectations with respect to the future movement of the CHF/EUR exchange rate might have an impact upon exports from Switzerland to the Eurozone and are thus a potential driver of the Swiss business cycle.

Yet, from an empirical perspective, finding a sufficient measure of exchange rate uncertainty remains a challenging task. While frequently used proxies have been historical volatilities and volatilities derived via Generalized Autoregressive Conditional Heteroscedasticity models (GARCH), as described, for instance, in Auboin and Ruta (2013), this study takes a new approach and derives a forward-looking measure of exchange rate uncertainty. Specifically, prices in FX derivative markets are used to estimate risk-adjusted option-implied density functions (RWDs). The RWDs are density forecasts, which reflect the market's views on the possible range and associated probabilities of future movements of the underlying exchange rate. The standard deviation and skewness of the RWDs can be used to construct forward-looking measures of uncertainty and directional expectations with respect to the future exchange rate. Conflicting evidence regarding the influence of exchange rate uncertainty on exports hinges on the possibility of nonlinearities in the propagation mechanism on exports, dependent upon the level of uncertainty. Correspondingly, a threshold VAR (T-VAR) framework is applied, which can distinguish high from low exchange rate uncertainty regimes. Within this framework, regime-dependent nonlinear impulse response functions of exports to shocks in the exchange rate, its uncertainty and directional expectations of future movements are analysed.

[1] Between 2003 and 2016, the average exports of goods to real GDP ratio was 35%, while exports of services account for roughly 17%. Within the same time span, 55% to 65% of the total monthly Swiss exports of goods went to the EU, while 80–90% of these exports went to Eurozone countries. (Source: author's own calculation based upon data provided by the Federal Statistical Office [FSO] and the Federal Customs Administration [FCA]).

The remainder of this chapter is organized as follows. Section 2 reviews the related uncertainty and exchange rate uncertainty literature. In section 3, the derivation of exchange rate uncertainty and directional expectation measures for the CHF/EUR exchange rate is described. The applied T-VAR methodology is presented in section 4. Section 5 provides the estimation results, while section 6 concludes.

2 Related Literature

The theoretical and empirical literature on exchange rate uncertainty is older compared to the relatively new and methodologically different uncertainty shock literature started by Bloom (2009). However, this paper tries to build a bridge between the two strands. Hence, this section reviews the relevant parts of both literature types and compares similarities and differences.

Focusing at first on exchange rate uncertainty, one finds that early theoretical work on its impact on exports is ambiguous. For instance, Clark (1973) argues that uncertainty about future exchange rates translates into uncertainty about future revenues in domestic currency and is therefore negative. In contrast, De Grauwe (1988) demonstrates that producers who have to decide whether to export or serve local markets will have disutility from increasing uncertainty, but may end up exporting more. If producers' marginal expected utility function of export revenues is convex with respect to the exchange rate, which appears under a sufficient degree of risk aversion, then higher variability of the exchange rate increases the marginal utility of export revenue. This effect is referred to as the income effect, while the substitution effect results from the disutility of increasing uncertainty. The substitution effect lowers the attractiveness of risky activities, such as exporting. The income effect works in the opposite direction. Hence, if the income effect dominates the substitution effect, a jump in the exchange rate uncertainty increases exports. Given that there are efficient forward markets, Baron (1976) argues that exchange rate uncertainty might be offset via hedging and therefore has no impact, but Caporale and Doroodian (1994) confirm that hedging generates costs and difficulties in terms of finding the optimal level of timing and volume. Theories described in Baldwin and Krugman (1989) and Dixit (1989) argue that an exporter's decision to enter or exit the international market can be seen as a real option. As uncertainty regarding the exchange rate increases, the option of entering becomes more valuable and less readily exercised. In contrast, due to sunk costs, firms that are already in the market remain there, even if there are large jumps in the exchange rate. Finally, Broll and Eckwert (1999) also take an option-based view on exports. They argue that when firms have access to a domestic market and the ability to store and pile up inventories, exchange rate uncertainty may enhance exports as it generates potential profits while potential losses are truncated due to the ability to walk away from exercising the export option.

In line with the conflicting predictions of the described theoretical models, the empirical evidence is inconclusive as well. Early studies, conducted by Cushman (1988), Chowdhury (1993) and Arize et al. (2000) and revisited by Zelekha and Bar-Efrat (2011), use historical real exchange rate volatility in univariate cointegration models and find negative short- and long-run effects of volatility on exports in the G7 countries, several developing countries and Israel. In contrast to those, McKenzie (1998) and Asteriou et al. (2016) measure real and nominal exchange rate volatility via GARCH models. The former study finds positive effects of exchange rate uncertainty on exports for Australia, while the latter finds no significant effect for Mexico, Nigeria or Turkey. In addition, by using a volatility measure derived from daily exchange rate data and a non-linear Poisson lag model, Baum et al. (2004) find a positive relationship between exchange rate uncertainty and exports for 13 developed economies. More recently, Rahman and Serletis (2009), Grier and Smallwood (2013), and Aye et al. (2015) use nonlinear GARCH-in-Mean VARs. The exchange rate uncertainty is measured as the conditional standard deviation of the forecast error of the exchange rate and is therefore estimated jointly with the other model parameters. By analysing the dynamic impact of first moment shocks in the exchange rate when it is controlled for uncertainty, they find that the impact on exports is larger compared to a linear model that does not take exchange rate uncertainty into account. In addition, Grier and Smallwood (2013) calculate quasi IRFs of an exchange rate uncertainty shock, which are unable to measure feedback between uncertainty and other variables, and find direct negative effects. Using firm-level data for China and Switzerland, Liu and Yan (2015) and Binding and Dibiasi (2017) find evidence for negative effects of exchange rate uncertainty shocks on investment for export-orientated firms. The shocks are analysed within event studies and caused by a switch of the exchange rate regime in China in 2005 and the discontinuation of the Swiss franc lower bound in January 2015.

The empirical literature described above mainly uses the volatility of the exchange rate as a proxy of uncertainty. However, uncertainty is a forward-looking concept and the applied methods are not able to take this property into account. The recently booming uncertainty shock literature has come up with a battery of general uncertainty proxies that are able to incorporate its forward-looking nature. In the following, the most commonly used measures are reported, while a more comprehensive overview can be found in Datta et al. (2017). Due to its availability, the most commonly used uncertainty proxies are asset market measures, especially stock market volatility indices (SVOL) like the Chicago Board Options Exchange Volatility Index (VIX). The idea is that uncertainty regarding macroeconomic performance should manifest itself in the option prices of stock option bundles, which provide insurance against large moves of the underlying stocks. The first to use this type of uncertainty proxy within a linear VAR framework is Bloom (2009). Another way of measuring uncertainty is conducted by Bachmann et al. (2013), Scotti (2016), and Ozturk and Sheng (2018), who derive uncertainty measures which are based on the expectation dispersion and surprises measured by forecast errors from business surveys (EDISP). A further measurement approach, implemented by Jurado et al. (2015) and Rossi and Sekhposyan (2015), is to derive the stochastic variation of the unforecastable part of the economy. The former study derives a macroeconomic uncertainty index (MU-I) by applying factor models to a large set of macro and financial variables, and using those to calculate the stochastic volatility of the unpredictable components of these time series. In contrast, the macro uncertainty index of Rossi and Sekhposyan (2015) (MU-II) only uses the GDP as a single time series. It is based on an ex ante forecast of GDP, whose error is compared to the ex post forecast error distribution. Conceptually and technically different are uncertainty indices, which are derived via text search procedures. The most prominent example is the economic policy uncertainty (EPU) index of Baker et al. (2016). This index counts the number of times the word "uncertainty" is used in combination with the words "economy" or "economic" and some policy-related terms in major newspapers. Most recently, Caldara and Iacoviello (2018) develop a geopolitical risk index (GPR), which analyses uncertainty with respect to another dimension, namely geopolitical tensions such as wars, natural disasters and terrorist attacks. Similar to the EPU, this broad-based index counts the number of articles in major newspapers around the world related to geopolitical risks.

Most of the mentioned uncertainty proxies are derived for single countries like the US or major countries in the EU. For instance, Meinen and Roehe (2017) derive or use five uncertainty indices (SVOL, EDISP, MU-I, MU-II and EPU) for the four largest economies of the EU. However, the Global Uncertainty Index (GUI) of Ozturk and Sheng (2018) and the GPR of Caldara and Iacoviello (2018) are derived as global measures for the whole world. The global nature of these two uncertainty proxies indicate that there are spillovers between countries. For example, Nowzohour and Stracca (2017) find a high correlation of several uncertainty proxies between 27 countries, while on a country level, the different uncertainty proxies are moderately correlated. This finding is also confirmed by Meinen and Roehe (2017) for the four largest economies in the EU.[2] A conclusion that can be drawn from these stylized facts is that the distinct uncertainty proxies actually analyse different types of uncertainty within a country and do not measure the same types. However, when the impact of exchange rate uncertainty is analysed on between country measures as exports, the cross-country spillovers have to be taken into account; otherwise, it is unclear whether a certain impact is due to heightened uncertainty in one country or the other.

To build a bridge between the general uncertainty shock literature and the strand of literature that analyses the impact of exchange rate uncertainty on exports, this study provides three major contributions. First, a new measure of nominal CHF/EUR exchange rate uncertainty is derived, which is forward-looking and moves countercyclically during periods of recessions and market turmoil. Therefore, it shares similar properties with commonly used uncertainty proxies such as the VIX. Second, while the (exchange rate) uncertainty literature mainly focuses on the second moment, the option-based approach is able to also provide information about higher-order moments such as the skewness as a measure of directional expectations. To the best of my knowledge, the only study that explores the impact of shocks to higher-order moments is

[2]Regarding the moderate correlation between uncertainty proxies, Nowzohour and Stracca (2017) find, for example, a value of 0.2 between EPU and SVOL measures. In the study of Meinen and Roehe (2017), the within country correlations span from 0.016 (EDISP vs EPU) to 0.704 (EPU vs SVOL).

Ferreira (2018), who analyses how stock market skewness affects the business cycle. Third, this study uses a threshold VAR framework, making it able to account and test for nonlinearities in the propagation mechanism of exchange rate uncertainty, an approach which has not been used so far in the exchange rate uncertainty literature. The inconclusive results within this literature indicate that qualitatively different impacts of uncertainty might occur due to the presence of multiple equilibria and associated states of the world. Therefore, exchange rate uncertainty shocks and directional expectation shocks might have qualitatively and quantitatively different implications for exporters when exchange rate uncertainty is high compared to more tranquil times, when it is relatively low. While T-VARs have been applied by Castelnuovo and Pellegrino (2018) in the general uncertainty literature, only monetary policy shocks during high and low uncertainty regimes have been analysed. Hence, this study enters new territory by measuring the impact of exchange rate level (first moment), exchange rate uncertainty (second moment) and directional expectations shocks (third moment) on exports, dependent upon whether uncertainty is high or low.

3 Measuring CHF/EUR Uncertainty and Directional Expectations

This section outlines the derivation of the uncertainty and directional expectation measures for the nominal CHF/EUR exchange rate, based on over-the-counter (OTC) market options.

3.1 Risk-Neutral Density Estimation

To derive the daily risk-neutral density (RND), the parametric method of Malz (1997) is used. Breeden and Litzenberger (1978) demonstrate that the RND is related to the price of a European call option at time t, with exercise price X and time to maturity $\tau = T - t$, by the discounted expected payoff of the option given by[3]

$$c(t, X, T) = e^{-r\tau} \int_X^{+\infty} (S_T - X)\pi_t^\tau(S_T)dS_T \tag{1}$$

In this setup, S_T denotes the exchange rate at the expiration date T, r the domestic risk free interest rate and $\pi_t^\tau(x)$ the time t RND of the exchange rate τ-months in the future. Taking the second derivative of (1) and rearranging terms yields

[3] A European call (put) option gives the buyer the right to buy (sell) the underlying asset at maturity for the pre-specified strike price X. The distance between the actual market price S_t and X determines the moneyness of the option. For $S_t = X$, the call option is said to be at-the-money (ATM) and for $S_t < X$ the call option is said to be out-of-the-money (OTM).

$$\pi_t^\tau(X) = e^{r\tau}\frac{\partial^2 c(t,X,T)}{\partial X^2} \tag{2}$$

Assuming that there exists a continuum of strike prices, the RND could simply be derived by approximating the derivative in (2) while taking finite differences of closely neighboured values of X. Unfortunately, such a continuum does not exist. Instead, FX options are traded in different bundles, which are constructed from put and call options that have the same maturity and moneyness. Moneyness is measured by the Black-Scholes (BS) call options delta: $\delta_c = e^{r_t^*\tau}\Phi[\frac{ln(\frac{S_t}{X})+(r_t-r_t^*+\sigma_t/2)\tau}{\sigma_t\sqrt{\tau}}] \in [0,1]$.[4] An at-the-money (ATM) call (put) option would have a $\delta_c = 0.5$. Therefore, the larger (smaller) the δ_c of a call (put) option is, the further out-of-the-money (OTM) it is. Typical levels for δ_c are 10%, 25% and 35%, where the 25δ market is the most liquid one. Moreover, instead of advertising the option bundle in terms of its monetary value, the convention in the OTC market is to quote the options price in terms of the BS implied volatility σ_t.

In contrast to the BS assumption of a constant σ_t for all possible values of X (and hence δ_c), σ_t tends to increase for options which are further OTM. This indicates that OTM options are more expensive than ATM options. The described phenomenon is known as the volatility smile (VS), and it violates the BS assumption of the implied RND being log-normal. In the σ-δ-space, the VS can be considered a u-shaped function $\sigma_t(\delta_c)$ with a minimum close to δ_c. Since the market is well aware of the existence of the VS, several option bundles that trade its properties have been developed. The most common ones are ATM-Straddles (atm_t), risk reversals ($rr_{25\delta,t}$) and butterflies ($bf_{25\delta,t}$).[5] These bundles trade the level, symmetry and curvature of the smile, respectively, which translate into the shape of the underlying RND. Malz (1997) uses the properties of those bundles for the 25δ market to approximate the VS by the following quadratic function:

$$\sigma_{25\delta,t}(\delta) = atm_t - 2rr_{25\delta,t}(\delta - 0.5) + 16bf_{25\delta,t}(\delta - 0.5)^2 \tag{3}$$

The BS delta function and equation (3) form a nonlinear system of equations, where the two unknowns are the strike price X and the corresponding value of $\sigma_{25\delta,t}$. By solving it numerically, the volatility smile is transformed from σ-δ-space to σ-X-space, making σ a function of a continuum of strike prices. The resulting function $\sigma_t(X)$ can be inserted into the BS formula

[4] Given the put options delta $\delta_p \in (0,1)$, put call parity implies $\delta_c = 1 - \delta_p$, making it possible to represent the moneyness of both put and call options by the call options delta.

[5] The atm_t combines the purchase of an ATM call and ATM put option. It becomes profitable whenever the exchange rate moves in either direction. The $rr_{25\delta,t}$ consists of an OTM put sell and an OTM call purchase, where both have a delta equal to 25%. It pays off when the exchange rate moves in one particular direction. The $bf_{25\delta,t}$ is constructed by an OTM put and call purchase and an atm_t sell. It becomes profitable when there is a large move of the exchange rate in either direction.

and the derivative in (2) can approximated by applying the second-order centralized difference quotient for a given step size h:[6]

$$\pi_t^\tau(X) = e^{r\tau}\frac{\partial^2 c(t,X,T)}{\partial X^2} \approx e^{r\tau}\frac{c(t,X+h,\tau)+c(t,X-h,\tau)-2c(t,X,\tau)}{h^2} \tag{4}$$

The method described above is used to calculate the daily option-implied RNDs between 2003:M10 and 2018:M10. The option data on ATM-straddles, risk reversals and butterflies for delta values of 25% are provided via Bloomberg on a daily basis up until 2016:M08. Afterwards the option data are downloaded via Thomson Reuters Eikon/Datastream. To proxy the domestic and foreign risk-free interest rates, the daily CHF and Euro Libor with matching maturities are used. The daily spot exchange rate is denominated in Swiss francs per Euro. The daily densities are estimated for the one-month and three-month maturities. Table B.2 in the appendix B summarizes the applied data.

3.2 Adjusting for Risk Aversion

Options are priced in a risk-neutral manner, meaning the probabilities given by the RND are calculated as if agents would only care about the expected value of the underlying asset. Therefore, the resulting RNDs deviate from the RWDs. However, Datta et al. (2017) argue that because real world investors are not risk-neutral, derivative-implied distributions contain information about risk preferences. Statistical techniques exist that use flexible calibration functions in which the parameters are estimated from RND-implied measures. Fackler and King (1990), de Vincent-Humphreys and Noss (2012), and Ivanova and Gutiérrez (2014), for instance, use beta distributions. The method applied here is based on those studies. Given a forward-looking horizon of τ-months, the exchange rate at maturity is $S_{t+22\tau}$. Assuming that the RNDs are the true density functions from which those exchange rates are drawn, Rosenblatt (1952) demonstrates that the probability integral transformations (PIT),

$$z_t = \int_0^{S_{t+22\tau}} \pi_t^\tau(x)dx = \Pi_t^\tau(S_{t+22\tau}), \tag{5}$$

are distributed according to a uniform distribution, such that $\{z_t^\tau(S_{t+22\tau})\}_{t=1}^T \sim iidU(0,1)$. The PITs have to be calculated from densities, which are distinct in maturities, because otherwise there would be built-in serial correlation in the z_t^τ-series. Since the RND does not account for risk aversion, it is unlikely to be the target distribution. However, assuming that the difference between the RND and RWD is systematic, there exists a differentiable calibration function, $C(\cdot) \in (0,1)$, which maps the RND, $\pi_t^\tau(x)$, into the RWD, $q_t^\tau(x)$. The mapping is given by

[6]MATLAB code is provided by Blake and Rule (2015) of the Bank of England.

$$q_t^\tau(X) = C'(\Pi_t^\tau(X))\pi_t^\tau(X) \tag{6}$$

where $C'(\Pi_t^\tau(X))$ is the calibration factor, obtained via the first derivative of $C(\cdot)$. A proper calibration function has to be very flexible to correct the RND for incorrect specifications in the location, dispersion, symmetry and curvature. Fackler and King (1990) propose the beta distribution, whose density is given by

$$c^B(z|j,k) = \frac{z^{j-1}(1-z)^{k-1}}{\int_0^z u^{j-1}(1-u)^{k-1}du}, \text{ for } z \in (0,1) \tag{7}$$

According to de Vincent-Humphreys and Noss (2012), this has a number of distinct advantages. First, it is parsimonious as it only depends on two parameters, j and k, but at the same time flexible enough to provide a variety of changes in the shape and location of the RND. Second, it nests the uniform distribution for $j = k = 1$; hence, if the RND is the correct target distribution, the beta is able to account for that.

The calibrated RWD would be the correct target density if the transformed series of PITs – $Q_t^\tau(z_t^\tau(S_{t+22\tau})) = C(\Pi_t^\tau(S_{t+22\tau})) = C(z_t^\tau(S_{t+22\tau}))$ – follows an iid uniform distribution. Hence, if $C(z \mid j,k)$ is the cumulative distribution function of a beta distribution, then the RND-implied PIT series are beta-distributed for given parameters of j and k. The optimal choice for the parameters j and k is obtained via maximum likelihood. The likelihood is given by the beta density, such that the maximization of the log likelihood function $log(L(j,k \mid z_t^\tau(S_{t+22\tau}))$ boils down to

$$(j^*,k^*) = argmax \sum_{t=1}^{N^\tau} log\left(\frac{z_t^\tau(S_{t+22\tau})^{j-1}(1-z_t^\tau(S_{t+22\tau}))^{k-1}}{\int_0^{z_t^\tau(S_{t+22\tau})} u^{j-1}(1-u)^{k-1}du}\right) \tag{8}$$

Given the optimal parameters (j^*, k^*), the RWD is calculated by applying equation (6). The RWDs are estimated for one- and three-month maturities. Between 2003:M10 and 2018:M10 there are $N = 3935$ estimated daily densities for each of the forecasting horizons. Because the densities are not allowed to overlap in maturities, the sample sizes reduce to $N^{1M} = 179$ and $N^{3M} = 59$. Given the observed time period, the sample size would shrink too much to get reliable estimates for longer maturities. The optimal calibration parameters (j^*, k^*) are presented in the appendix table B.1.

3.3 Construction of the CHF/EUR Uncertainty and Directional Expectations Measures

The two forward-looking option-implied measures used in the following are the standard deviation of the RWD as a time-varying measure of market uncertainty and the RWDs' skewness as a measure of directional expectations. Directional expectations can be measured by the skewness as it describes the asymmetry of the risk-adjusted density forecast. When it is positive, more probability mass is shifted towards its right tail, resulting in higher probabilities assigned to larger values of the CHF/EUR exchange rate and therefore in a depreciation expectation. It would also be conceivable to use the excess kurtosis as a measure of uncertainty, as it is a measure of the market's assessment towards large swings in any direction. However, later discussed tests for threshold effects show no evidence in this regard. Therefore, this study does not use the fourth moment. For a τ-months forecasting horizon, the corresponding formulas are given by

$$sd_t^\tau = \sqrt{E[(X - E[X])^2]} = \sqrt{\int_0^{+\infty} (x - E[X])^2 q_t^\tau(x) dx} \tag{9}$$

and

$$sk_t^\tau = E\left[\left(\frac{X - E[X]}{sd_t^\tau}\right)^3\right] = \int_0^{+\infty} \frac{(X - E[X])^3}{(sd_t^\tau)^3} q_t^\tau(x) dx \tag{10}$$

These daily time series are aggregated to the monthly level by taking the mean of all sd_t^τ and sk_t^τ realizations for each month. This provides smoothing and therefore mitigates noise. However, theories described by Kozlowski et al. (2015) argue that extreme events are rare and therefore most informative about the underlying data generating process. Therefore, in a robustness check later on, aggregation is also done by taking the maximum realization of each month. As the main forecast horizon, a maturity of $\tau = 1M$ is chosen for three reasons. First, according to Datta et al. (2017), for $\tau = 1M$, FX option markets are most liquid. Second, given the comparably large number of non-overlapping PITs for the one-month forward-looking horizon, estimates of the beta distribution coefficients are likely to be most accurate. Third, among many uncertainty measures, the one-month forward-looking horizon is a common choice.[7]

When analysing the impact of exchange rate uncertainty on exports, one has to take into account that different uncertainty proxies are correlated across countries (see, Meinen and Roehe (2017)). Therefore, a reduction of exports due to a jump in the option-implied standard de-

[7] For example, the VXO/VIX and all its country-specific relatives are measured as one-month forward-looking measures. The macro uncertainty index of Jurado et al. (2015) is also derived for the one-month forward-looking horizon.

viation might also occur due to heightened Eurozone-specific uncertainty. To take Eurozone-specific uncertainty into account, different types of proxies are aggregated to generate a synthetic Euro area uncertainty measure. The specific proxies are the VSTOXX, as a measure for general uncertainty within the Eurozone; the European economic policy uncertainty index (EEPU); and the composite indicator of systemic stress (CISS) as a measure of financial strain within the Eurozone. More specifically, the CISS sub-index which accounts for stress within the financial intermediary sector is used. It is included because times of financial stress, and therefore tightened credit conditions, often coincide with times of heightened uncertainty.[8] In addition, to account for a broader set of uncertainty shocks from outside the Eurozone, the geopolitical risk index (GPR) of Caldara and Iacoviello (2018) is also taken into account. The described measures have been chosen because they account for a broad set of different uncertainty types and are available for a long time span. Time series plots for sd_t^{1M}, sk_t^{1M}, sd_t^{3M}, sk_t^{3M}, $VSTOXX_t$, $EEPU_t$, $CISS_t$ and GPR_t can be found in Figure A.1 in the appendix A, while data sources can be found in Table B.2, in the appendix B.

One can see a clear co-movement between sd_t^{1M} and the Eurozone-specific measures of uncertainty. Orthogonalizing sd_t^{1M} with respect to uncertainty spillovers from the Eurozone by regressing it on all four Eurozone uncertainty measures leads the slope coefficients of $CISS_t$ and GPR_t to be insignificant. A possible explanation might be a common factor driving the Eurozone uncertainty. Given the moderate correlation between uncertainty proxies on a country level, Nowzohour and Stracca (2017) use the first principal component as the underlying trend across different dimensions of uncertainty. In line with this approach, this paper also uses the first principal component $\phi_{1,t}^{EU}$ as the common factor driving the Eurozone uncertainty.[9] Figure A.1 in the appendix reveals the co-movement between $\phi_{1,t}^{EU}$ and sd_t^{1M}. To get the purged measure of exchange rate uncertainty, the following regression is estimated:

$$sd_t^{1M} = \alpha + \beta\phi_{1,t}^{EU} + \phi_t^{1M} \tag{11}$$

The residual of (11), ϕ_t^{1M}, serves as the orthogonal component of exchange rate uncertainty, which is free of uncertainty spillovers from the Eurozone. The purged uncertainty measure and option-implied skewness are plotted against real exports of goods from Switzerland to the Eurozone in Figure A.1 in the appendix. One can see that the exchange rate uncertainty moves countercyclically, while the skewness shows a tendency to move procyclically, a finding con-

[8]The focus relies upon this sub-index as it already accounts for 30% of the total compound CISS, while other dimensions as for example equity market stress (15%) and stress in bond markets for non-financial firms (15%) are already taken into account by the VSTOXX. The correlation between financial stress indicators has been documented, for instance, by Stock and Watson (2012), who find a large correlation between credit spreads and uncertainty proxies.

[9]To get a more precise and comprehensive estimate of the underlying trend, the chosen time span for the PCA analysis is from 1999:M02 to 2018:M10, which is the maximum for these series, restricted by the availability of the VSTOXX.

firmed by Ferreira (2018), who finds that stock market skewness tracks the GDP in the US.

4 The Threshold Vector Autoregressive Methodology

4.1 Setup and Identification of the Threshold Vector Autoregression

The threshold VAR methodology applied in this paper follows Tsay (1998) and Balke (2000). The model is given by the following system:

$$\begin{aligned}\mathbf{x^l_t} &= \alpha^{\mathbf{1}} + \mathbf{A^1 x^l_t} + \mathbf{B^1(L) x^l_{t-1}} + \mathbf{C^1(L) x^f_{t-1}} + \epsilon^{\mathbf{1}}_{\mathbf{t}} \\ &\quad + [\alpha^{\mathbf{2}} + \mathbf{A^2 x^l_t} + \mathbf{B^2(L) x^l_{t-1}} + \mathbf{C^2(L) x^f_{t-1}} + \epsilon^{\mathbf{2}}_{\mathbf{t}}]\, \boldsymbol{I}[\phi^{1M}_{t-d} > \gamma] \end{aligned} \tag{12}$$

where $\mathbf{x^l_t}$ is a vector of local (endogenous) variables and $\mathbf{x^f_t}$ is a vector of exogenous (foreign) variables. The system is split into two separate VARs. Switching between the two VARs is achieved by the indicator function $I[\cdot]$. It takes the value 1 whenever the d-lagged threshold variable, which is the exchange rate uncertainty measure ϕ^{1M}_{t-d} described in section 3.3, crosses the threshold γ and zero otherwise. The regime-dependent dynamics of the system are described by the lag polynomial matrices $\mathbf{B^1(L)}$, $\mathbf{C^1(L)}$, $\mathbf{B^2(L)}$ and $\mathbf{C^2(L)}$. Regime-specific intercepts are given by the vectors $\alpha^{\mathbf{1}}$ and $\alpha^{\mathbf{2}}$, while the corresponding vectors of structural residuals are given by $\epsilon^{\mathbf{1}}_{\mathbf{t}}$ and $\epsilon^{\mathbf{2}}_{\mathbf{t}}$. They are assumed to follow $\epsilon^{\mathbf{i}}_{\mathbf{t}} \sim N(\mathbf{0}, \mathbf{\Sigma^i})$, for i=1, 2. Hence, by having regime-dependent covariance matrices, they can account for heteroscedasticity with respect to the two regimes. The matrices $\mathbf{A^1}$ and $\mathbf{A^2}$ contain the regime-specific contemporaneous relationships.

The endogenous vector $\mathbf{x^l_t}$ contains the following variables between 2003:M10 and 2018:M10: real exports of goods from Switzerland to the Eurozone (exp_t) and the Swiss CPI (cpi_t), with the latter included to take domestic price reactions into account.[10] Furthermore the three-month Libor (i_t), which is the target rate of the SNB, is included to measure monetary policy reactions.[11] To control for first moment shocks and therefore level effects of exchange rate changes, the nominal CHF/EUR spot exchange rate (s_t) is used. The time series of the RWDs' skewness (sk^{1M}_t) is included to quantify directional expectation shocks (third moment). Uncertainty shocks (second moment) are measured by the exchange rate uncertainty measure (ϕ^{1M}_t), which is also used as the threshold variable. The exogenous vector x^f_t contains the following global

[10] It should be noted that within the observed time span Slovenia (2007), Malta (2008), Cyprus (2008), Slovakia (2009), Estonia (2011), Latvia (2014) and Lithuania (2015) entered the Eurozone. However, the combined share of real exports of goods from Switzerland to these counties in 2003 and 2017 compared to the amount of exports to all other Eurozone counties is between 1% and 2% for each year. Therefore, the accession of those countries to the Eurozone has no significant impact on the export time series. The numbers have been derived with data provided by the Federal Customs Administration of Switzerland.

[11] The SNB conducts monetary policy by fixing the 3M-Libor via liquidity-providing and liquidity-absorbing money market transactions (see `https://www.snb.ch/en/ifor/public/qas/id/qas_gp_strat#`).

and Eurozone-specific variables: the Eurocoin index (y_t^*), a real-time and forward-looking business cycle indicator for the Eurozone to proxy foreign demand for Swiss products, and the CPI for the Eurozone (cpi_t^*), to measure foreign price reactions. Commodity prices are taken into account by the CRB index (crb_t). Finally, to control for European monetary policy, the shadow short rate (ssr_t) of Krippner (2015) for the Eurozone is included. The variables in x_t^l and x_t^f are transformed to stationarity if necessary via first differences. Related information, including data sources and unit root tests, are summarized in the appendix in Table B.2. It turns out that the null of non-stationarity cannot be rejected for cpi_t^*, crb_t, ssr_t ,exp_t ,cpi_t, i_t and s_t, while y_t^*, sk_t^{1M} and ϕ_t^{1M} are stationary. In addition to the standard Dickey-Fuller test, the threshold variable is tested for stationarity by the Enders and Granger (1998) threshold unit root test. This is particularly important, as the threshold variable ϕ_t^{1M} drives the non-linear dynamics of the T-VAR model described below and must be stationary under the non-linear specification. The final vector of foreign and local variables is:
$\mathbf{x_t} = (\mathbf{x_t^l}, \mathbf{x_t^f})' = (\Delta exp_t, \Delta cpi_t, \Delta i_t, \Delta s_t, sk_t^{1M}, \phi_t^{1M}, y_t^*, \Delta cpi_t^*, \Delta crb_t, \Delta ssr_t)'$.

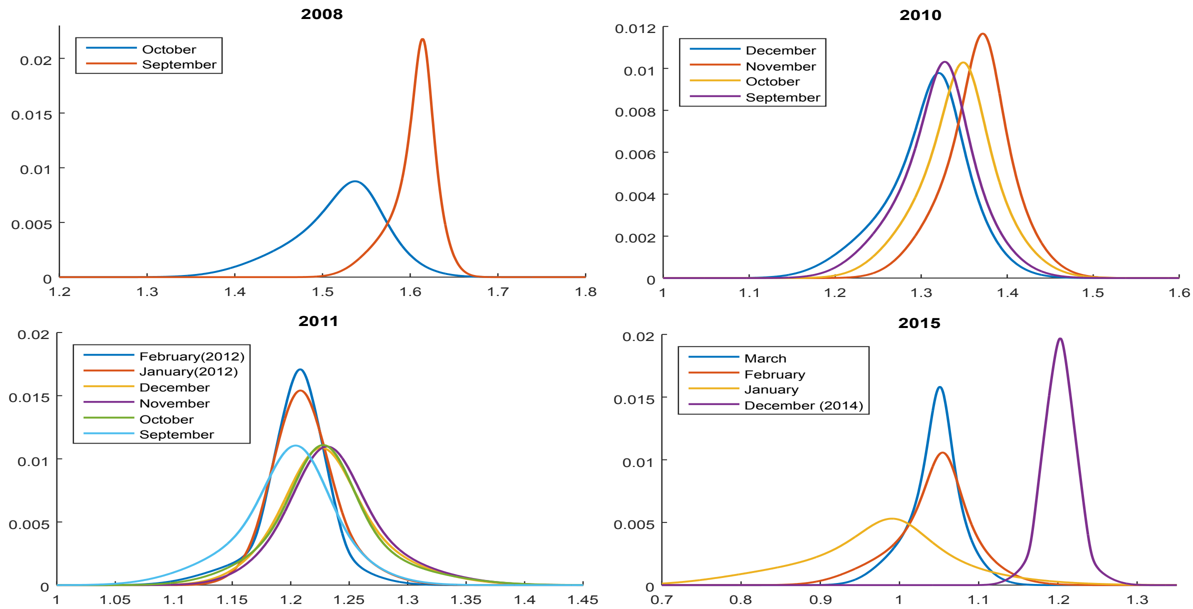
To identify the shocks, a Cholesky decomposition of the regime-dependent covariance matrices is applied. This implies that the contemporaneous matrices $\mathbf{A^1}$ and $\mathbf{A^2}$ exhibit a lower triangular recursive structure, in which the ordering of the variables has implications for the behaviour of the system.[12] Specifically, it implies that s_t, sk_t^{1M} and ϕ_t^{1M} react contemporaneously to shocks of all local macro variables, which is makes sense because those are fast-moving financial variables. Exports react with a lag to shocks in all local variables, implying that the economy needs some time to adjust to movements of financial market variables and monetary policy rates. This assumption can be defended on the grounds that contracts are not adjusted immediately and need some time to be re-negotiated after conditions change. Monetary policy, measured by the three-month Libor rate i_t, reacts contemporaneously to exports and prices, while it is assumed that it reacts with a lag to the fast-moving exchange rate, skewness and exchange rate uncertainty. Finally, the ordering of the fast-moving financial variables s_t, sk_t^{1M} and σ_t^{1M} needs some further justification. Because the Swiss franc is a safe haven asset, it might be the case that an increase in the exchange rate uncertainty measure is always related to an appreciation of the CHF and a change in the skewness, making a distinction difficult. Fortunately for the RWDs, this is not the case. The correlation between the sd_t^{1M} time series and the spot exchange rate is -0.125. For a distinction between first and third moment shocks, it is even less critical as the correlation between s_t and sk_t^{1M} is with -0.043 negligible. Finally, the correlation between sd_t^{1M} and sk_t^{1M} is -0.082. Therefore, the third moment evolves nearly independent from the first two moments.[13]

[12] The identification via Cholesky decomposition with the applied ordering of variables is in line with recursive identification schemes in the uncertainty shock literature (see, for instance, Jurado et al. (2015), or Meinen and Roehe (2017)).

[13] Admittedly, for the T-VAR analysis, purged standard deviations are used, but the sd_t^{1M} time series remains the cornerstone of the uncertainty measure, resulting in a still informative analysis of the correlation structure between s_t, sd_t^{1M} and sk_t^{1M}.

To further highlight the distinction between first and second moment shocks, Figure 1 presents RWDs for four selected events during which major uncertainty shocks occurred.[14] Comparing September 2008 to October 2008 in the upper left panel, one can see that first and second moment shocks appear simultaneously. This pattern is different in 2010 when the Euro crisis was mounting. The upper right panel shows that between September 2010 and December 2010 there is almost no change in the standard deviation, while the exchange rate is quite volatile. Focusing on 2011, after the Swiss franc floor was introduced in September, the lower left panel shows that between September and October the CHF depreciated from 1.20 to 1.25, but there is no decrease in the standard deviation observable. However, between January 2012 and February 2012, the CHF appreciated back to values of 1.20, while the uncertainty decreases. This indicates that uncertainty and level movements are not always negatively related. Finally, the level and standard deviation shock in January 2015 after the discontinuation of the Swiss franc floor is shown in the lower right panel. Here one can see a clear co-movement between the exchange rate and the standard deviation, but in the months after the peg got discontinued and the exchange rate stabilized, one can see a decrease in the standard deviation between February 2015 and March 2015, while the exchange rate movement is negligible. To summarize, the visual inspection of the densities during certain events and the parallel investigation of the correlation structure reveals that it is possible to identify exchange rate uncertainty shocks and changes in the directional expectations while simultaneously controlling for first moment shocks and ordering the uncertainty measure after the exchange rate.

Figure 1: Risk-adjusted densities before and after selected uncertainty shocks



[14] Fist moment shocks can be demonstrated with the RWDs' location, because movements of the exchange rate would result in an adjustment of the market's forecast.

4.2 Hypothesis Testing and Estimation of the Threshold Vector Autoregression

Before a dynamic analysis of (12) is conducted, the data should be tested for the presence of multivariate threshold nonlinearity. When the threshold γ is known, the existence of two separate regimes could be tested by the joint hypothesis $\mathbf{A^2} = \mathbf{B^2(L)} = \mathbf{C^2(L)} = \mathbf{0}$. Unfortunately, it is unknown and has to be estimated, which causes the problem that the standard Wald-test and F-test would have non-standard distributions. This happens because under the null hypothesis of linearity the threshold γ would not be identified. To account for this so-called nuisance parameter problem, two separate test procedures are conducted. The first one is the arranged regression test of Tsay (1998), which transforms the threshold model into a change point problem. The data get rearranged according to an increasing order of the threshold variable ϕ^{1M}_{t-d}. Under the null of linearity, the residuals of the rearranged regression would be correlated with the regressors of the system. Due to the rearrangement, an F-test for the parameter matrix of the system, in which the predictive residuals are regressed on the vector of target variables x^l_t, would asymptotically follow a $\mathcal{X}^2$-distribution. The second test procedure is suggested by Andrews and Ploberger (1994) and Balke (2000). Instead of transforming the system into a change point problem, which would obtain standard inference, Andrews and Ploberger (1994) suggest using three separate test statistics, sup-$Wald$, avg-$Wald$ and exp-$Wald$, in which the critical values of these test statistics are generated by the fixed regressor bootstrap of Hansen (1996).

Finally, the VAR lag L, the threshold lag d and the threshold γ are estimated jointly via AIC. For various combinations of L and d, the corresponding threshold variable ϕ^{1M}_{t-d} is ordered and the model is estimated via maximum likelihood for the respectively defined subsamples and for each possible realization of ϕ^{1M}_{t-d}. To have a minimum set of data in each regime and to prevent overfitting, the top and bottom 15% of the realizations plus number of parameters for an individual equation of the model are left out as potential thresholds.[15] In a robustness check, different trimming values are provided later on. The optimal combination of the lag length $\hat{L}$, the threshold lag $\hat{d}$ and the threshold value $\hat{\gamma}$ is selected by the values of the set $\{L, d, \gamma\}$, which minimizes the AIC.

4.3 Nonlinear Impulse Response Functions

The threshold nonlinearity implies that the IRFs are no longer independent of the initial history ω_{t-1}, the size (ψ) or the sign of the shock they are calculated for. Building upon Koop et al. (1996), the dynamic impacts of structural shocks to the exchange rate, the uncertainty and the skewness, are given by the nonlinear impulse response functions (NIRF):

[15] This choice of 15% trimming is a common one in the T-VAR literature. See, for instance, Hansen (1999), Hansen (2000), Tsay (1998), Calza and Sousa (2006), Hubrich and Teräsvirta (2013), and Evgenidis and Tsagkanos (2017).

$$NIRF(h, \psi, \omega_{\mathbf{t}}) = E[\mathbf{x}^{\mathbf{l}}_{\mathbf{t+h}} | \psi, \omega_{\mathbf{t-1}}] - E[\mathbf{x}^{\mathbf{l}}_{\mathbf{t+h}} | \omega_{\mathbf{t-1}}] \tag{13}$$

NIRFs have to be estimated via simulation. Taking an initial history $\omega_{\mathbf{t-1}}$ for all variables in the T-VAR, two paths of the system are simulated by loading the model with bootstrapped residuals. In one of the two paths, a shock ψ is imposed in h=0. Repeating this procedure N=500 times, taking the average of the two paths and subtracting them from each other yields the NIRFs conditional upon $\omega_{\mathbf{t-1}}$. To derive state-dependent NIRFs, the bootstrap described above is applied to histories which belong to either the high or low uncertainty state. Given the subsample of histories that belongs to one of these two uncertainty states, M=500 initial conditions are randomly drawn from this subsample. Finally, for each of the resulting M NIRFs, the average is formed. Confidence bands are derived by taking quantiles of the $M * N$=25,000 simulated NIRFs.

5 Results

5.1 Nonlinearity Tests and Model Estimation

Table 1 displays the estimation results of the threshold value, the threshold lag and the VAR lag length, as well as the described nonlinearity tests. The estimated threshold is $\hat{\gamma} = 0.3419$, with a corresponding threshold lag of $\hat{d} = 1$ and a VAR lag length of $\hat{L} = 1$

Table 1: Threshold nonlinearity test, threshold, threshold lag and VAR lag estimation

Threshold	*Tsay (1998)*	*Andrews and Ploberger (1994)/Balke (2000)*		
$\hat{\gamma} = 0.3419$				
Threshold Lag	*C(1)*	*Sup-Wald*	*Avg-Wald*	*Exp-Wald*
$\hat{d} = 1$	**97.62**	**166.09**	91.92	**78.47**
VAR Lag	**(0.007)**	**(0.021)**	(0.300)	**(0.023)**
$\hat{L} = 1$				

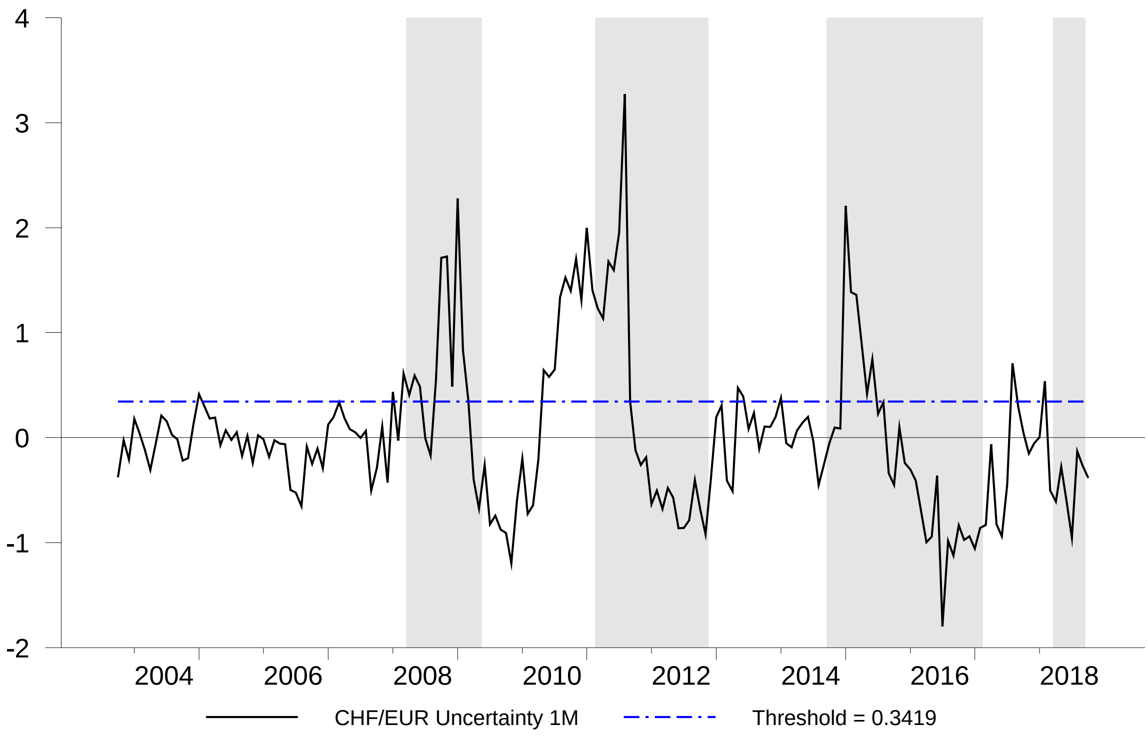
Notes: : The left column shows the results of the threshold, threshold lag and VAR lag estimation, which are jointly selected via AIC for all possible values of the threshold variable (excluding 15% trimming). The column second from the left displays the results for the arranged regression test of Tsay (1998), where $C(1)$ is the test statistic calculated for one threshold lag. The three rightmost columns show the Sup-$Wald$, Avg-$Wald$ and Exp-$Wald$ test statistics of Andrews and Ploberger (1994) and Balke (2000). P-values are derived via the fixed regressor bootstrap of Hansen (1996). The number of bootstrap replications is $N = 500$.

The nonlinearity test of Tsay (1998) clearly rejects the null hypothesis of linearity at the 5% significance level. In line with the Tsay (1998) test, the simulation-based tests of Andrews and Ploberger (1994) and Balke (2000) indicate that the null hypothesis of no threshold nonlinearity is rejected at the 5% significance level for three of the four test statistics. Therefore, the nonlinearity tests provide strong evidence in favour of a threshold model.

Figure 2 plots the one-month forward-looking CHF/EUR uncertainty measure, which is purged from spillovers caused by uncertainty and financial stress in the Eurozone and by global uncertainty. Grey-shaded areas highlight recessionary periods in Switzerland, as classified by the OECD. It is apparent that the exchange rate uncertainty jumps over the threshold of 0.3419 during periods of financial and economic turmoil. The following peaks are to be emphasized. In October 2008, there is a large jump of the uncertainty measure far above its threshold, which can be linked to the upcoming global financial crisis of 2008/2009. Until early 2010, the uncertainty decreases significantly. However, from May 2010 until September 2011, the uncertainty measure exceeds its threshold again. This period of high uncertainty corresponds to events during the Euro crisis. To be emphasized would be the agreement between the Eurozone states and the IMF about a bailout package for Greece in the amount of 110 billion Euro in May 2010. Furthermore, in November 2010, the EU and the IMF agreed upon a bailout package for Ireland in the amount of 85 billion Euro. The largest peaks can be observed between July and September 2011, Portugal required bailing out with a 78-billion-Euro package and a second bailout package for Greece in the amount of 109 billion Euro. The uncertainty measure reaches its highest value to date in August 2011 after the former EU Commission president José Manuel Barroso warned that the sovereign debt crisis may spread beyond the periphery of the Eurozone. After the implementation of the one-sided target zone of 1.2 Swiss francs per Euro in September 2011, the exchange rate uncertainty decreases significantly. The uncertainty measure remains in the low uncertainty state most of the time until January 2015. This is an indication that the peg was considered credible and there was certainty about the attitude of the SNB towards the future path of the CHF/EUR exchange rate.[16] Another large jump in the exchange rate uncertainty can be observed in January 2015, when the lower bound policy of the CHF/EUR exchange rate was surprisingly discontinued.

[16] See chapter Funke et al. (2017) for a more detailed discussion of the credibility of the one-sided target zone.

Figure 2: One-month forward-looking CHF/EUR exchange rate uncertainty



Notes: The black line shows the standardized monthly series of the one-month forward-looking uncertainty measure for the CHF/EUR spot exchange rate. The blue line shows the estimated threshold value of 0.3419. Whenever the standardized uncertainty measure exceeds the threshold, it is counted as a period of heightened uncertainty. Grey-shaded areas represent periods of recessions in Switzerland, as classified by the OECD.

Compared to the unpurged RWDs' standard deviation presented in Figure A.1, in the appendix A, the purged exchange rate uncertainty is lower. The reason is that the Eurozone uncertainty jumps parallel to the option-implied standard deviation. Hence, a fraction of the jump in the standard deviation can be explained by large uncertainty spillovers, which means that the purged exchange rate uncertainty presented in Figure 2 is smaller. In contrast to that, Figure A.1 illustrates that for August 2011 the option-implied standard deviation jumps one month prior to the Eurozone uncertainty, while for January 2015 the Eurozone uncertainty does not jump at all. Therefore, there are no strong contemporaneous spillovers and the jumps in the standard deviation actually reflect pure exchange rate uncertainty, leading to a purged uncertainty measure that is similar in magnitude compared to the option-implied standard deviation.

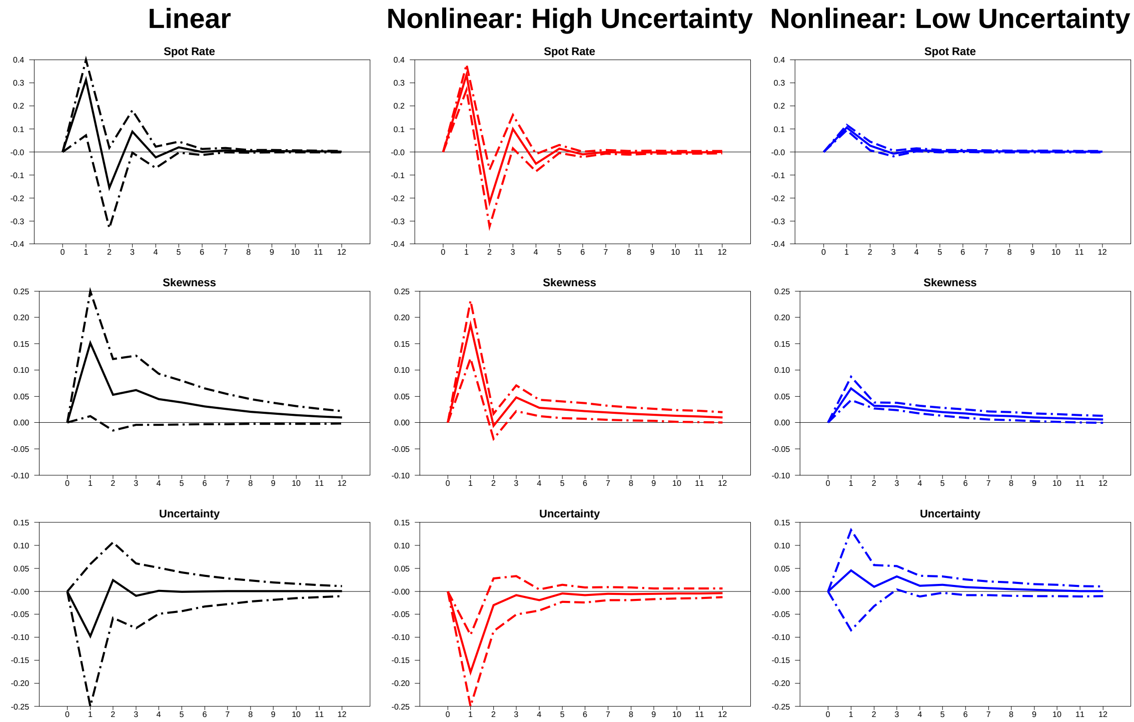
5.2 Impulse Response Analysis

Figure 3 shows the NIRFs of exports to the Eurozone to a one-standard-deviation shock in the CHF/EUR exchange rate itself; the directional expectations, measured by the RWDs skewness; and the uncertainty, measured by the purged standard deviation of the RWD. The nonlinear IRFs of the T-VAR are compared to the linear IRFs of a standard VAR that is estimated for the same variables, while the lag length has again been selected by AIC.

A first moment shock, measured by a sudden jump in the exchange rate itself, corresponds to a depreciation of the CHF against the Euro. In the high uncertainty regime, a first moment shock increases exports significantly after one month by roughly 0.35 percent. In the following months, the response quickly bounces back to its previous level. During the low uncertainty regime, a first moment shock exhibits slightly different dynamics. A positive and significant response of exports to the Eurozone by 0.1 percent appears one month after the depreciation of the Swiss franc against the Euro and stays significant for another month. Compared to the high exchange rate uncertainty regime, the reaction of exports is less than half as strong. One possible explanation for this comes from the different volatilities of the CHF/EUR exchange rate during the two uncertainty regimes. As uncertainty coincides with times of market turmoil, the movements of the CHF against the Euro are larger due to its safe haven status, therefore causing exporters to respond more strongly. Comparing the results to the IRF derived from the linear model shows that the dynamics are closer to the high uncertainty regime in terms of magnitude but can in general be seen as an average across the two regimes.

A shock to the directional expectations with respect to the movement of the Swiss franc against the Euro is measured by a sudden jump of the option-implied skewness. A positive shift of the skewness would result in a change in market sentiment towards a depreciation of the CHF against the Euro within the next month. Qualitatively, the high and low uncertainty regime responses of exports to the Eurozone are similar. However, the response is more pronounced during the high uncertainty regime. When the skewness jumps, exports increase significantly after one month by 0.2 percent. The effect declines over time, but stays significant for the rest of the year. In the low uncertainty regime, exports react less strongly as the largest significant peak is 0.065 percent after one month. Similar to the high exchange rate uncertainty regime, the impact on exports to the Eurozone declines after the initial jump but stays significant for the next twelve months. With the Euro as an invoice currency, an expected depreciation of the Swiss franc would result in an expected rise of future profits for exporters. A higher valuation of future profits and an increasing demand for Swiss products, as prices measured in Euro are expected to fall, would give an incentive for exporters to increase exports in the near future. Similar to a first moment shock, the dampened effect of directional expectations during times of low uncertainty can be observed because the expected range of possible realizations of the CHF/EUR exchange rate is smaller compared to the high uncertainty state. Comparing the results with the IRFs of a linear model shows that in terms of magnitude and persistence it can be seen as an average across the high and low uncertainty regime.

Figure 3: Linear IRFs and nonlinear regime-dependent IRFs of exports to the Eurozone

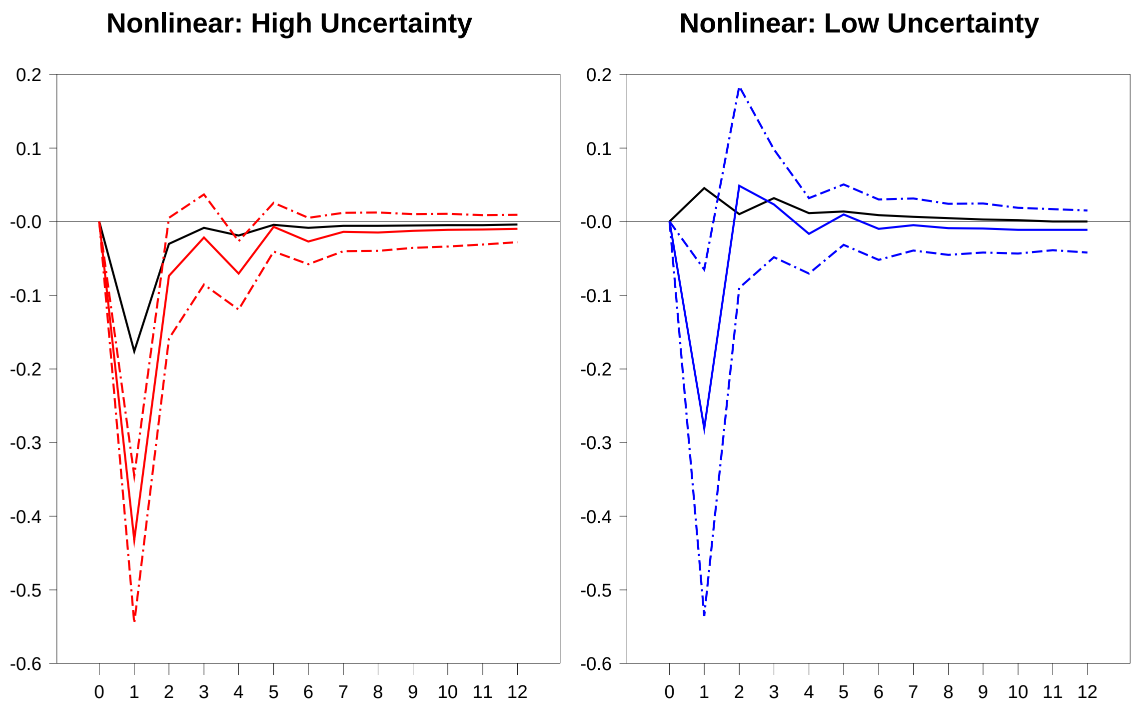


Notes: The left panel shows the IRFs of a linear VAR, while the middle and right panels show the regime-dependent nonlinear IRFs of the T-VAR. Solid lines represent the mean IRFs to a one-standard-deviation shock in the exchange rate, the skewness and the exchange rate uncertainty measure. Dashed lines represent 68% confidence bands derived from the NIRF bootstrap for the T-VAR and posterior quantiles, derived via a flat prior for the linear VAR. The lag length for the linear VAR is selected via AIC and corresponds to L=1. For the T-VAR, the mean IRFs have been calculated with the bootstrap of Koop et al. (1996) for $N = 500$ replications and $M = 500$ randomly drawn histories.

Next, the impact of a CHF/EUR exchange rate uncertainty shock on exports to the Eurozone is analysed. During times of high uncertainty, an exchange rate uncertainty shock generates a significant decline of exports by roughly 0.18 percent after one month. Afterwards, exports quickly bounce back to their previous level. The adverse effect of exchange rate uncertainty can arise through both the demand and supply channels. Consumers and investors from the Eurozone might postpone spending when there is the possibility of large moves of the exchange rate, while Swiss firms might reduce the supply as future profits become more uncertain. However, during times of low CHF/EUR exchange rate uncertainty one can observe that an uncertainty shock leads to a significant positive response of exports in the amount of 0.04 percent in the third month. As already discussed in the literature review, the evidence of the effects of exchange rate uncertainty is inconclusive, from both a theoretical and an empirical perspective. The results derived here indicate that whether exchange rate uncertainty affects exports positively or negatively depends on the level of uncertainty itself. During times of low uncertainty, which coincide with more stable market environments, an increase in the expected volatility might be seen as a chance to increase profits for exporting firms. As the Swiss franc is a safe haven asset, it tends to appreciate during times of high uncertainty, which reduces foreign demand and decreases profits of exporters. However, when uncertainty is low, the expected safe haven appreciation might be less pronounced or even absent, leading exporters to focus more on the potential chances of a larger expected range of exchange rate realizations compared to the potential risks. Within the theoretical literature, De Grauwe (1988) and Broll and Eckwert (1999) discuss that sufficiently risk-averse exporters will have disutility from increasing uncertainty but may end up exporting more. De Grauwe (1988) argues that firms have to decide to allocate the goods they want to sell either to domestic or to foreign markets. If the utility gain of potentially rising profits overcompensates the disutility of increased uncertainty, then the firm will increase its international activity. In addition, the study by Broll and Eckwert (1999) takes a growth option argument and states that uncertainty enhances exports when there is the ability to shift products towards local markets or pile up inventories. While potential losses are truncated due to the ability to walk away from exercising the export option, an increase in uncertainty generates potential profits. The NIRFs suggest that these positive effects only occur when the market environment is not too uncertain and Switzerland itself is not in a recession. During times of high uncertainty and market turmoil, the potential negative effects are clearly dominant. Comparing the nonlinear with the linear IRFs reveals that there is only a negative response exports, which is less pronounced compared to the high uncertainty regime response and is also insignificant. Again, this appears because the linear model averages across the two regimes.

While there is consensus in the general uncertainty shock literature about the dominant negative impacts of uncertainty on real activity, the picture is different for exchange rate uncertainty and exports. The presented positive response of exports due to exchange rate uncertainty shocks may guide policy makers to the conclusion that potentially negative effects of erratic policy changes can be partially offset by the positive effects of heightened uncertainty. Therefore, it is worth investigating what happens when a large exchange rate uncertainty shock hits the economy during times of high and low uncertainty. The largest uncertainty peak occurred in August 2011 during the European debt crisis. It corresponds roughly to a three-standard-deviation shock. Figure 4 presents the corresponding NIRFs, occurring after a three-standard-deviation shock; the baseline results are also plotted as solid black lines for comparison.

Figure 4: Nonlinear regime-dependent IRFs of exports to the Eurozone to a large exchange rate uncertainty shock

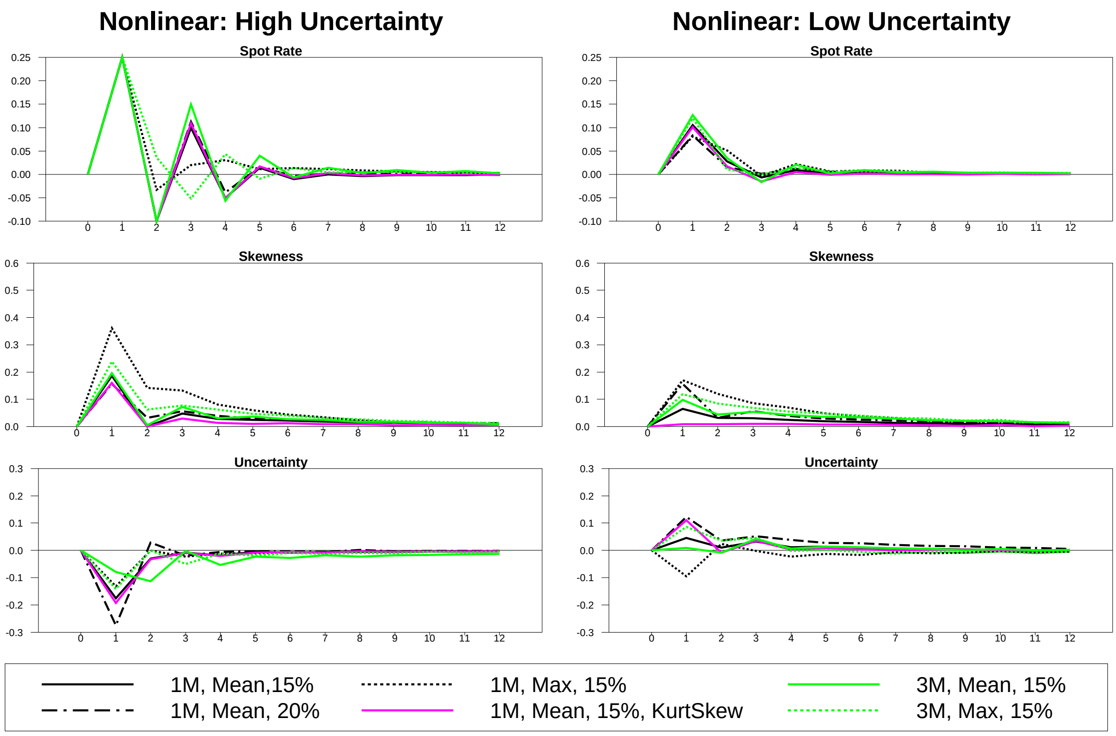


Notes: Black lines represent the baseline NIRFs for a one-standard-deviation exchange rate uncertainty shock. Solid red and blue lines represent the NIRFs due to a three-standard-deviation exchange rate uncertainty shock. The corresponding red and blue dashed lines represent the 68% confidence bands.

When a large CHF/EUR uncertainty shock hits the economy in the high uncertainty regime, exports to the Eurozone react significantly negative by -0.42 percent. Compared to the one-standard-deviation shock, the negative response of exports is roughly three times larger. However, during low uncertainty times, a large exchange rate uncertainty shock also causes a significant negative reaction, which is around -0.28 percent. Therefore, policy makers can no longer exploit the positive response of exports due to exchange rate uncertainty during tranquil times. The conclusion that can be drawn from this is that policy makers should avoid actions which cause large uncertainty swings, as even during times of low uncertainty there is the risk that exports will get depressed.

To demonstrate robustness, Figure 5 shows the NIRFs of exports for different specifications of the T-VAR. Explicitly, in the baseline specification a trimming value of 20% instead of 15% is used. Additionally the uncertainty measure and the skewness have been aggregated from daily to monthly frequency by using each month's maximum value instead of the monthly mean. Furthermore, the baseline results are contrasted with a specification in which, instead of a one-month forward-looking horizon, a three-month horizon is chosen in the derivation of the uncertainty and the skewness, for both the mean and the maximum value aggregation. Finally, in the baseline specification, the skewness is replaced by an interaction term between the skewness and the excess kurtosis. The kurtosis increases whenever large moves in any direction are expected. The resulting interacted series serves as a measure of pronounced directional expectations, as positive (negative) skewness together with increasing kurtosis would mean that the market expects a depreciation (appreciation) and that this movement is expected to be large.

Figure 5: Nonlinear regime-dependent IRFs of exports to the Eurozone for different specifications of the T-VAR



Changing the trimming value to 20% in the baseline specification does not have a strong impact, as the nonlinear IRFs are very close to the baseline. Comparing the baseline case with a specification that uses the maximum value instead of the mean in the aggregation of the standard deviation and the skewness again shows very similar results. However, the positive effects of exchange rate uncertainty are absent in the low uncertainty state, which can be explained by the fact that shocks are larger and drive the system faster into the high uncertainty state. Shocks to the directional expectations are qualitatively similar when the maximum aggregation is applied, but tend to be larger in both regimes. This result is also unsurprising, as the expected range of CHF/EUR fluctuations is larger, making directional expectations stronger as well. Using a three-month forward-looking horizon for the option-based measures shows that the responses tend to be of similar size and shape compared to a one-month horizon. Finally, when the skewness is interacted with the kurtosis in the baseline, one can see that first, second and third moment shocks exhibit similar reactions of exports. To summarize, one can verify the robustness of the results.

6 Conclusion

This paper derives forward-looking measures of uncertainty and directional expectations for the CHF/EUR exchange rate by using OTC market options. The resulting uncertainty measure, which is purged from uncertainty spillovers from the Eurozone, shows countercyclical movements as it peaks during times of economic turmoil and unstable market environments. It is therefore able to define a high and a low uncertainty regime. The option-based approach is able to distinguish first from second moment shocks, which is not possible with the commonly used conditional volatility approach. Using a nonlinear T-VAR model, it is investigated whether exchange rate uncertainty and directional expectations play a role for Switzerland, as it is a small open economy that depends upon international trade. By applying nonlinear impulse response analysis, it is found that the reaction of exports to shocks in the exchange rate itself, directional expectations and the exchange rate uncertainty are asymmetric with respect to the high and low uncertainty regimes. In particular, the mixed findings regarding the impact of uncertainty on exports frequently reported in the literature can be explained by the presence of different uncertainty regimes.

A potential field for future research might be the application of the methods described here to a broader set of currencies. Particularly, the derivation of an effective exchange rate uncertainty index would be possible, which would enable the researcher to analyse the effect of exchange rate uncertainty exports as a whole. Moreover, the applied methods can be used for different countries.

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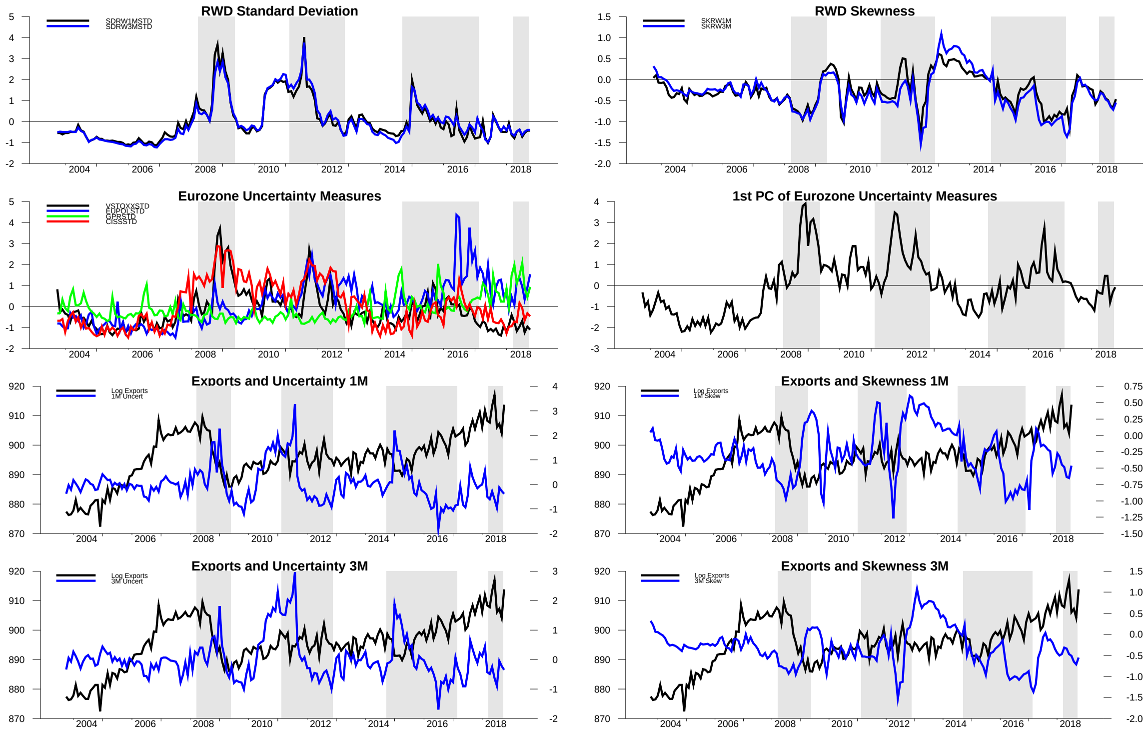
Appendix

A Figures

Figure A.1: Option-implied standard deviation, skewness, Eurozone uncertainty measures and their first principal components, log-exports



Notes: The grey-shaded areas represent periods of recessions in Switzerland, as classified by the OECD. All CHF/EUR and Eurozone-specific uncertainty measures are standardized.

B Tables

Table B.1: Parameter estimates for beta distribution given non-overlapping PITs

j	k
τ =1M	
0.9471	**1.0206**
(0.0919)	(0.1008)
$\tau = 3M$	
1.1078	**1.1032**
(0.1896)	(0.1869)

Notes: Standard errors in parentheses. The PITs used must be non-overlapping in maturities. Therefore, the number of observations decreased from $N = 3935$ to $N^{1M} = 179$ and $N^{3M} = 59$.

Table B.2: Applied data, data sources and unit root tests

	Variable Information			ADF-Test	
	Variable	Time Span	Source	Levels	Diff
Option Data and Risk Free Interest Rates for RWD Estimation	atm_t	2003:M10 to 2018:M10 (Daily)	Bloomberg	—	—
	$rr_{25\delta,t}$		Bloomberg	—	—
	$bf_{25\delta,t}$		Bloomberg	—	—
	i_t		Bloomberg	—	—
	i_t^*		Bloomberg	—	—
	s_t		Bloomberg	—	—
Eurozone Uncertainty Measure	$VSTOXX_t$	1999:M02 to 2018:M10 (Monthly)	Datastream	**-4.493****	—
	$EEPU_t$		Datastream	-2.439	—
	$CISS_t$		Datastream	-2.241	—
	GPR_t		Auth-page	**-4.424****	—
	$\phi_{1,t}^{EU}$		Own calc	**-3.569****	—
T-VAR Variables	y_t^*	2003:M10 to 2018:M10 (Monthly)	BOI	**-3.118***	—
	cpi_t^*		Datastream	-2.062	**-6.407****
	crb_t		Datastream	-2.154	**-11.19****
	ssr_t		Auth-page	-1.114	**-5.461****
	exp_t		FCA/FSO	-1.935	**-10.44****
	cpi_t		Datastream	-2.380	**-3.655****
	i_t		Bloomberg	-0.987	**-8.262****
	s_t		Bloomberg	-0.744	**-15.80****
	sk_t^{1M}		Own calc	**-4.435****	—
	ϕ_t^{1M}		Own calc	**-3.870****	—
	sk_t^{3M}		Own calc	**-3.607****	—
	ϕ_t^{3M}		Own calc	**-3.649****	—
	sd_t^{1M}		Own calc	**-3.400***	—
	sd_t^{3M}		Own calc	**-3.970****	—

	Enders and Granger Test	
	Threshold	Test Value
ϕ_t^{1M}	0.3419	**7.490****
ϕ_t^{3M}	0.2716	**5.852***

Notes: "Own calc" means own calculation. BOI is the Bank of Italy data warehouse. "Auth-page" means author's web page. FCA and FSO are the data warehouses of the Federal Customs Administration and the Federal Statistical Office of Switzerland. Real exports of goods from Switzerland to the Eurozone exp_t have been calculated by deflating the seasonally adjusted nominal exports, provided by the FCA, with the export price index, provided by the FSO. All series with a seasonal pattern are corrected for that by the respective data suppliers. For the Augmented Dickey-Fuller test, we have H_0 : $UnitRoot$ vs. H_1 : $Stationary$. The ADF-tests contain a constant. Critical values are -2.8786 for 5% (*) and -3.4696 for 1% (**). The lag length of augmentation lags is chosen automatically by AIC. The ADF test has only been conducted for variables for which the stationarity is required in the actual application. Therefore, the option variables have not been tested for stationarity, as their integration order is irrelevant for the RWD calculation. Since the first differences of the Eurozone and global uncertainty proxies, as well as their first principal component, are not used, the ADF-test is skipped. The same is true for σ_t^{1M}, σ_t^{3M}, sk_t^{1M}, sk_t^{3M} and y_t^*.

The Enders-Granger procedure tests for the presence of unit roots, when the time series is assumed to follow a threshold autoregression. The null hypothesis is $H_0 : UnitRoot$ vs. $H_1 : Stationary$. The number of augmentation lags is set to $K = 1$, as in the T-VAR. Critical values are taken from Enders (2001) and are 6.34 for 5% (**) and 5.55 for 10% (*). The thresholds correspond to those estimated for the T-VAR.