Swiss National Bank communication and investors' uncertainty

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Abstract

This paper analyzes the effects of Swiss National Bank communication on stock investors' uncertainty. Monetary policy news is identified via changes in short- and medium-term futures prices as well as by applying methods from computational linguistics and dictionary approaches to SNB policy statements. Surprises in policy rate changes and regarding the future path of the policy rate exhibit an asymmetric effect on stock investors' uncertainty. Moreover, by taking into account varying topics the SNB addresses in its statements, I show that investors' uncertainty decreases due to an optimistic tone in communications about economic growth. Increased uncertainty expressed in SNB statements translate into increasing stock investors' uncertainty. The results explain how news contained in monetary policy statements reduce noise in financial markets and therefore contribute to financial stability.

Keywords: Monetary policy, communication, stock markets, uncertainty

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1 Introduction

Central bank communication has a profound impact on financial markets. While previous research established that monetary policy communications affect asset markets, the exact mechanism is not yet fully understood (Hansen and McMahon 2016b). Since central banks address various issues in their communications, the question remains whether discussions about inflation, macroeconomic activity, or financial market related issues affect financial market outcomes.

Central bank communication can affect market outcomes through "creating news", when changes in communication are reflected in market prices, and through "reducing noise", i.e. communication reduces market volatility by reducing financial market investors' uncertainty (Blinder et al. 2008). Volatility is reduced through one or more of the following channels. First, with discussions on (expected) macroeconomic conditions, central banks signal likely future policy actions and therefore reduce market uncertainty about the future path of the policy rate. Second, assuming asymmetric information between the central bank and the private sector regarding macroeconomic fundamentals, i.e. central banks might have superior information about the state of the economy (Romer and Romer 2000), communication reduces this asymmetry and signals the central bank's view on macroeconomic aggregates (signaling channel).[2] Related to this channel, communication might function as a focal point for market participants reducing strategic uncertainty. In other words, communication increases investors' confidence about higher order beliefs. It coordinates expectations by reducing uncertainty about others' expectations about macroeconomic fundamentals (coordination channel). In order to derive an optimal communication design it is crucial to understand the transmission of central bank communication to market uncertainty. This is important in the light of the discussion of monetary policy as a tool to fulfill macroprudential tasks and therefore to contribute to financial stability.

This paper investigates the effect of Swiss National Bank (SNB) policy rate changes and communication on Swiss stock market investors' uncertainty. Uncertainty is measured as abnormal stock market variance derived from the Swiss Market Index (SMI). Monetary policy news are identified using changes in short- and medium-term futures prices as well as applying techniques from natural language processing to SNB statements. More specifically, Latent Dirichlet Allocation (LDA) is employed in order to identify topics the SNB discusses in its press releases and introductory statements of press conferences. Additionally, the topic-specific tone is measured using a dictionary approach (Jegadeesh and Wu 2017). This allows addressing the following questions: Does market uncertainty respond to positive communication about inflation or do negative discussions of global or domestic economic activity lead to changes in stock investors' uncertainty? When the SNB talks uncertainly about financial market conditions, how does market uncertainty respond?

Investigating the effect of SNB communication on market uncertainty is important for the following reasons. As a small open economy, the Swiss economy might be more affected by

[2] For a theoretical investigation of the signaling channel, compare Tang (2015) or Melosi (2016), among others.

international monetary policy transmissions and global economic activity than larger economies. It is important to evaluate the success of SNB communication in influencing market outcomes under these circumstances. Moreover, since the SNB follows a dual mandate of pursuing price stability and stabilizing the Swiss franc to other major currencies, it is important to investigate how effective the SNB is in communicating concerns about exchange rate developments (See Burkhard and Fischer 2009).

The results indicate that unexpected policy rate cuts decrease stock investors' uncertainty. Unexpected communication indicating a lower future path of the policy rate, however, increases stock investors' uncertainty. For both effects, the results suggest that stock investors distinguish between positive and negative surprises, i.e. there is evidence for an asymmetric response of investors' uncertainty to policy rate and path surprises. Moreover, some topics discussed in SNB statements are more informative to stock investors than others and therefore affect their uncertainty. More specifically, optimism in growth-related discussions reduces stock investors' uncertainty by coordinating their expectations. This finding has important implications for the design of monetary policy communication if the central bank has an explicit financial stability mandate.

The paper contributes to the existing literature in the following ways. The paper sheds light on which policy news, contained in central bank communication, matter for stock investors' uncertainty to change. This helps clarifying the role of central bank communication in restoring confidence, e.g. by reducing uncertainty, which is especially important for the role of central banks in financial or economic crises. In general, the findings of this paper contribute to the discussion on optimal central bank communication, which is an important aspect in the debate of how central bank design can improve policy outcomes (Reis 2013).

There is vast amount of empirical evidence that monetary policy communication affects volatility in financial markets. Most studies, however, concentrate on the question if it affects volatility and by how much it does. Only recently, more studies investigate the content and topics discussed and evaluate its effect on market volatility (Born et al. 2014, Picault and Renault 2017, Ehrmann and Talmi 2017 and Jegadeesh and Wu 2017 among others). For the case of the SNB, Burkhard and Fischer (2009) and Ranaldo and Rossi (2010) investigate the effect of communication on asset markets. Both find that communication is an important tool for central banks to affect asset prices and expectations, especially at the zero (or effective) lower bound. Building on these papers, I ask which of the topics the SNB addresses are more important than others in affecting stock investors' uncertainty.

The reminder of the paper is organized as follows. Section 2 presents the data. In Section 3, the methods and specifications are introduced. Section 4 discusses the results while section 5 concludes.

2 Data

The sample contains data on all SNB monetary policy decisions between January 2000 and December 2016. All press releases and introductory statements of press conferences following the decisions are collected.[3] The SNB changed its policy regime from monetary to inflation targeting at the end of 1999 that is why monetary policy decisions before 1999 are excluded from the analysis.

The SNB decides upon monetary policy quarterly in March, June, September, and December. After each monetary policy decision, the SNB publishes a press release communicating the reasons behind the decision. After the policy decision in June and December, however, the SNB additionally holds a press conference to communicate the decision to the public. In addition to these scheduled meetings each quarter, the SNB unfrequently decides upon monetary policy on unscheduled meetings. Overall, this results in 84 policy events (PE), where 67 are scheduled and 17 are unscheduled. On 35 PE, the SNB holds a press conference following its decision. Since the SNB provides substantially more information in press conferences, I assume that market participants pay more attention to the press conference than to the corresponding press release the same day. Thus, the sample contains (a) press releases whenever there was no press conference and (b) the introductory statements of the chair of the SNB Governing Board whenever there was a press conference. As a result, 49 press releases and 35 introductory statements enter the analysis.

In what follows, m denotes days with PE and t all trading days. For each PE, I extract quantitative and qualitative monetary policy news contained in SNB statements. First, I extract the SNB's current year inflation forecast, denoted as π^f_{1m}, and the inflation forecasts for the following two years (π^f_{2m}, π^f_{3m}). Second, the SNB's GDP forecasts for the current year (y^f_{1m}) and for the upcoming year are extracted (y^f_{2m}). Third, qualitative news contained in statements is measured by employing a dictionary approach as well as a topic model approach (see methods below).

Financial market data comprise changes in the implied rate of Euroswiss spot futures prices as well as of maturities of three month traded on LIFFE. Futures prices are used to calculate unexpected policy rate changes and changes in expectations about the future path of the policy rate. Furthermore, to calculate expected and abnormal stock market variance, two daily variance measures are used. First, I use the daily index of option implied volatility based on the Swiss Market Index (the VSMI). The VSMI reflects expected volatility based on option trading with a horizon of thirty calendar days or 22 trading days, respectively. Second, daily realized variance is calculated using squared 5-minute returns of the Swiss Market Index (SMI).[4]

3 Methods

In this section, I first outline how abnormal stock market variance is calculated, which serves as the measure of stock investors' uncertainty. Second, the methodology for how policy rate and path surprises are measured is presented. Third, I provide an intuition of the Latent Dirichlet Allocation (LDA) applied to SNB statements and show how the information is used to construct topic-tone scores, which are used in event-study regressions. Fourth, forecasts and

[3] See http://www.snb.ch/en/ifor/media/id/media_releases.

[4] Intra-day data on the SMI was kindly provided by the SIX Swiss Exchange AG.

control variables are reported. Finally, the specifications are presented.

3.1 Abnormal stock market variance as a measure of uncertainty

In order to investigate wether SNB communication on PE days affects stock investors' uncertainty in a causal way, it is necessary to compare actual stock market variance to expected variance. The latter reflects predicted variance that would have occurred without the policy news of the PE. A measure of expected stock market variance can be obtained following the two-variable projection as proposed by Bekaert et al. (2013).[5] Realized variance of the SMI is regressed on the lagged squared option implied volatility (VSMI) and lagged realized variance as follows:

$$RVAR_t = \alpha + \beta_1 VSMI^2_{t-22} + \beta_2 RVAR_{t-22} + e_t, \tag{1}$$

where $RVAR_t$ denotes monthly realized variance on day t, which is calculated as the sum of squared five-minute returns.[6] All variables are expressed in monthly percentages squared.
The forecasting model in (1) is estimated using all trading days t except PE days as well as ten trading days before and after all PE days [-10 days; +10 days]. Standard errors are corrected for serial autocorrelation using 30 Newey and West (1987) lags. As in Bekaert et al. (2013), the top one percent of observations is winsorized before estimating (1). The results are, however, very similar using an unwinsorized sample. Results of this forecasting exercise are provided in Appendix A. $\widehat{RVAR}_m$ denotes the fitted values of this regression serving as a measure of expected stock market variance, which is an out-of-sample forecast of expected variance on PE m. The difference between actual and expected variance on PE days m measures abnormal variance due to the policy event and proxies uncertainty. Formally, abnormal variance is computed as

$$AV_m = RVAR_m - \widehat{RVAR}_m, \tag{2}$$

and cumulative abnormal variance is calculated as

$$CAV_m^D = \sum_{d=1}^{D} AV_{m+d-1}, \tag{3}$$

where d is an integer running from 1 to $D = \{1, 2, 3, 4, 5, 10\}$. D denotes the number of trading days for which abnormal variance is cumulated after the PE m. For instance, CAV_m^5 sums up AV_m on the PE day m and AV_m on each of the four days after. In the following, CAV_m^D is used to investigate whether SNB communication exhibits a persistent effect on stock investors' uncertainty.

[5] Bekaert et al. (2013) compare eight volatility forecasting models with different predictors. The model selection criteria are out-of-sample root mean squared error, mean absolute errors and stability (through the recent financial crisis). According to this evaluation, the authors choose the model presented above.

[6] As a robustness check, I use information on opening, high low and closing prices of the SMI to calculate $RVAR_t$, which are freely available for most stock indices. Unbiased and efficient measures of daily realized variance using this information are proposed by Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991), among others. Results employing these measures of realized variance in (1) indicate, however, that intra-day data are needed to obtain a fine measure of realized variance.

3.2 SNB monetary policy rate and slope surprises

Monetary policy rate surprises are measured following Kuttner (2001). One-day changes of the spot-month Euroswiss futures rate proxy unexpected changes in the SNB policy rate. Formally, this proxy is given by

$$\Delta \tilde{r}^u_m = \Delta f^0_m = f^0_m - f^0_{m-1}, \tag{4}$$

where f^0_m is the implied rate of the spot-month futures at the end of PE day m and f^0_{m-1} is the implied rate of the spot futures the previous day. Furthermore, surprises concerning the future path of the policy rate are proxied by the variation in daily changes of the three-month Euroswiss futures, which is not explained by daily changes in the spot-month futures. This "slope-surprise" is obtained as the residual of the regression

$$\Delta f^3_m = \alpha + \beta \Delta f^0_m + slope_m, \tag{5}$$

where $\Delta f^3_m = f^3_m - f^3_{m-1}$.[7] The regression purifies the changes in the longer-term futures rate from the level effect of the short-term futures changes and allows to measure market surprises in the expected path of the policy rate (Neuhierl and Weber 2016). While the recursive regression scheme proposed in Gürkaynak (2005) allows calculating $slope_m$ only for scheduled PE, the simple regression in (5) allows it for all PE. In order to not lose the 17 unscheduled PE of the sample for the analysis, (5) is used instead of the recursive regression scheme.[8]

3.3 Extracting topics and tone from SNB statements

The content of SNB communication is captured by extracting the topics and tone of each monetary policy statement. While the tone is measured by a dictionary approach, i.e. counting words with positive, negative, and uncertain connotation, topics are captured using LDA, a topic model approach.

LDA allows finding clusters of words, i.e. recurring patterns of co-occurring words, in a large corpus of texts. It allows to identify how much content of a given SNB statement is dedicated to a certain topic. The LDA algorithm assigns each word w of the set of SNB statements m to one of a pre-specified number of topics $k = 1, 2, 3, ...K$. In brief, the algorithm compares the occurrence of topics within a statement to how a word has been assigned in other statements and searches for the best match. It is important to note that "LDA is a bag-of-words model in which the order of words does not matter, just their frequencies. While this assumption clearly throws away information, it is a useful simplification when the primary consideration is to measure the topics a statement covers (Hansen et al. 2015)." Appendix C provides details on the LDA algorithm. For an extensive elaboration of LDA and its extensions, see Blei and Lafferty (2009).

Before LDA is applied to SNB statements, the raw texts are preprocessed in the following way.

[7] Results are robust using daily changes of the four-month Euroswiss futures, i.e. $\Delta f^4_m = f^4_m - f^4_{m-1}$.

[8] Employing the recursive regression scheme leads to no significant results, which might be mainly driven by the fact that 17 observations are lost in this case.

First, each statement is split into its paragraphs (See Jegadeesh and Wu 2017). This allows a more precise association of the topic-tone relations (see below).[9] When splitting statements into paragraphs, very few paragraphs are excluded because they do not discuss issues related to monetary policy. For instance, on the 10/12/2015, the SNB expressed its opinion on the Swiss sovereign money initiative (Vollgeldinitiative) in the last paragraphs of its statement. On the 16/06/2016, the SNB provided information about its new webpage "Our National Bank". Since these paragraphs do not contain information about monetary policy, they are excluded from the analysis. Overall, I obtain $p = 1068$ monetary policy related paragraphs in the $m = 84$ statements.

Second, in each paragraph, capital letters are changed to lower cases. All numbers, punctuations, common stopwords such as *in*, *the* or *at* as well as names such as *Thomas Jordan* or *SNB* are removed. Words occurring only once in the whole corpus of statements are excluded. Excluding the very frequent stopwords and very infrequent words ensures that LDA concentrates on words with informational content, which are used across statements to generate the latent topics. This leads to a better performance of the LDA. If a word is only used once in 84 statements, it is unlikely that it drives the verbalization of a certain topic across statements. Finally, the remaining words are stemmed to their common linguistic root. For instance, the words *changing*, *changes* and *changed* all become *change*.

The preprocessed paragraphs serve as the main input to the LDA algorithm next to a predefined number of topics K to be estimated. Regarding the optimal choice of K, interpretability of the word-to-topic associations might be more important than relying on model selection techniques, such as out-of-sample prediction accuracy (Blei 2012). Estimating LDA on paragraphs with low k leads to very broad topics (clusters), which reflect the main discussion on the corpus. As K increases, topics become more specific or even subtopics are formed, which might be grouped together since they have similar word associations (such as in Hansen and McMahon 2016a or Jegadeesh and Wu 2017). In order to strike the balance between isolating each topic and still have interpretable results, I follow the choice of Jegadeesh and Wu (2017) and Saret and Mitra (2016) and set $K = 8$. As a robustness check, I estimate LDA with $K = 7$ and $K = 9$.

The tone of each SNB statement is measured based on a dictionary approach such as in Tetlock et al. (2008). The number of all positive, negative, and uncertainty words is counted according to the classification provided in the financial tonal list developed by Loughran and McDonald (2011).[10] The statement-level nettone (NT_m) and uncertainty (UN_m) are calculated to capture

[9] Hansen and McMahon (2016a) go one step further and split their texts into sentences. Paragraphs of SNB statements are, however, mostly quite short containing only a couple of sentences. Therefore, the difference between a "sentence level" analysis and "paragraph-level" analysis should be negligible. Second, paragraphs are mostly set to distinguish different topics from one another. Using this additional information helps the LDA algorithm to obtain the distinct topics.

[10] The word list employed is available under `http://www3.nd.edu/~mcdonald/Word_Lists.html`. There exist two alternatives to this word list. First, words associated with expansion and contraction could be employed (See Apel and Blix Grimaldi 2014). It is unclear, however, how this words should be used in the inflation context. Signs of "increasing" or "decreasing" inflationary pressure can be "good" or "bad" news depending on the level of current inflation compared to the target of two percent. For this reason, I avoid using this word list. Second, Picault and Renault (2017) propose a field-specific lexicon for ECB communication by relying on a term-weighting and contiguous sequence of words (n-grams) approach. They show that their measure outperforms the dictionaries

the general tone of each SNB statement. NT_m is defined as the number of all positive words minus negative words divided by the total number of words of each statement m. Similarly, UN_m is defined as the number of uncertainty words divided by the total number of words in each statement m. These measures, however, do not answer the question whether the SNB communicates negatively in terms of inflation or economic activity. In order to measure topic-specific tone, the dictionary approach is combined with the results of the LDA procedure. The output of the LDA algorithm provides estimates of topic proportions $\hat{\theta}_p = [\hat{\theta}_p^1, ..., \hat{\theta}_p^8]'$ for each paragraph p. In other words, LDA calculates which of the $K = 8$ topics is discussed in which proportion in each paragraph. These topic proportions are combined with the tone of the corresponding paragraph as in Jegadeesh and Wu (2017). The topic-specific tone and uncertainty is measured by calculating nettone scores (NTS) and uncertainty scores (US) as

$$NTS_p^k = \hat{\theta}_p^k * NT_p \tag{6}$$

and

$$US_p^k = \hat{\theta}_p^k * U_p, \tag{7}$$

where $\hat{\theta}_p^k$ is the proportion of topic k in paragraph p obtained from the LDA procedure and NT_p is the number of positive words minus the number of negative words (nettone) in p. U_p denotes the number of uncertainty words in p. These paragraph-specific scores for each k are aggregated for each statement m as

$$NTS_m^k = \sum\nolimits_{p=1}^{P_m} NTS_p^k * (\frac{1}{L_p}), \tag{8}$$

where P_m is the number of paragraphs in statement m and L_p is the number of words in paragraph p. Thus, each paragraph-specific score gets weighted by the inverse of the paragraph length. The intuition is that longer paragraphs are down-weighted because they are more difficult to read and the information they contain is more difficult to process. US_p^k is aggregated in exactly the same way. Appendix D provides an example for the calculation of these scores.

3.4 SNB forecasts

Beside qualitative news about the SNB's macroeconomic outlook, statements of scheduled PE also contain quantitative forecasts of inflation and GDP. The SNB communicates a conditional inflation forecast π_{im}^f for the current year ($i = 1$), as well as for the two following years ($i = 2, 3$). The forecast is conditional in the sense that it is made under the assumption that the respective policy rate is constant over the forecast horizon. Since π_{1m}^f, π_{2m}^f and π_{3m}^f are highly correlated (between 0.57 and 0.78), I summarize π_{2m}^f and π_{3m}^f in the measure

$$d\pi_{23m}^f = (\frac{\pi_{2m}^f + \pi_{3m}^f}{2}) - 2. \tag{9}$$

proposed by Loughran and McDonald (2011) and Apel and Blix Grimaldi (2014). The approach is, however, prone to subjectivity and coding errors, since statements are coded manually in an initial step.

In contrast to π^f_{1m}, which measures the SNB's current year inflation expectations, $d\pi^f_{23m}$ captures whether the SNB expects to meet its target of two percent annual inflation in the medium-term. Moreover, the SNB communicates a GDP forecast y^f_{im} for the current year ($i = 1$) and, in the statement after the monetary policy decision in December, additionally a forecast for the upcoming year (y^f_{2m}). Since y^f_{2m} is not communicated on three out of four scheduled PE, only y^f_{1m} is used in the event-study regressions.

3.5 Control variables

Aside from SNB actions and communication, surprises in economic data might also affect investors' uncertainty on PE days. In order to account for the possible effect of economic news surprises on uncertainty, I use the normalized Citi Economic Surprise Index for Switzerland denoted as S_m. The index is calculated on a daily basis as a three-month rolling window and aggregates a range of different data surprises (actual data release versus Bloomberg survey median prior to the release). S_m is available since January 2003 onward and is set to zero between 2000 and 2002 to prevent loosing observations. S_m controls for daily changes in the general macroeconomic condition due to economic data surprises.

Furthermore, investors' uncertainty might be more pronounced during the recent financial crisis. Therefore, the dummy variable $crisis_m$, which is equal to one for the years 2007 to 2009 and zero otherwise, controls for this possibly different effect on uncertainty. Moreover, on PE days in June and December the SNB holds press conferences after the monetary policy decision and corresponding publication of the press release. To control for the potentially different impact on stock market uncertainty, the dummy variable pc_m, which is equal to one on PE days with a press conference and zero otherwise, controls for the effect of press conferences. Finally, since there are 17 unscheduled PE in the sample, the dummy variable us_m controls for the possibly different impact of unscheduled PE on uncertainty.

3.6 Specifications

In an event study setting, cumulative abnormal variance is regressed on monetary policy news. As a benchmark specification, market based measures of policy surprises are used to explain stock investors' uncertainty on PE days. The regression takes the form

$$CAV^D_m = \alpha + \beta_1 \Delta\tilde{r}^u_m + \beta_2 slope_m + \beta_3 us_m + \beta_4 S_m + \beta_5 crisis_m + \beta_6 pc_m + e_m, \qquad (10)$$

where $\Delta\tilde{r}^u_m$ and $slope_m$ are defined as described in 3.2 and us_m, S_m, $crisis_m$, and pc_m are defined as outlined in 3.5.

As previous research indicates, the reaction of market sentiment to monetary policy surprises might be asymmetric (see Kurov 2010, Kurov 2012). This suggests that stock investors' uncertainty might be affected differently by unexpected expansionary than by unexpected contractionary policy. To test the possible asymmetric impact, (10) is extended by including $P_{1m}\Delta\tilde{r}^u_m + (1 - P_{1m})\Delta\tilde{r}^u_m$, $P_{2m} slope_m + (1 - P_{2m}) slope_m$, and $P_{3m} S_m + (1 - P_{3m}) S_m$ instead of $\Delta\tilde{r}_m^u$, $slope_m$ and S_m, where P_{1m}, P_{2m}, and P_{3m} are dummy variables equal to one if the corresponding surprise is positive and zero otherwise.

Using only $\Delta\tilde{r}_m^u$ and $slope_m$ from futures contracts to account for unexpected changes in monetary policy on PE days is motivated by the finding of Gürkaynak et al. (2005): "...financial markets nonetheless have reacted as if there is essentially one additional degree of information beyond the surprise change in federal funds rate target". This approach, however, does not answer the question which of the policy news contained in SNB statements leads to changes in expectations about the future path of the policy rate expressed in $slope_m$ and which of the news affects stock market uncertainty (CAV_m^D). The multi-dimensionality of central bank communication calls for a more detailed analysis of policy news contained in statements.

Therefore, in a third step, monetary policy news extracted from SNB statements are added to (10) instead of $slope_m$ to investigate whether uncertainty responds differently to forecasts or the expressed nettone and uncertainty. In a first step, statement-level nettone (NT_m) and uncertainty (UN_m) are used to investigate if stock investors' uncertainty reacts to the general tone and uncertainty expressed in SNB statements. The specification takes the form

$$CAV_m^D = \alpha + \beta_1 \Delta\tilde{r}_m^u + \beta_2 \pi_{1m}^f + \beta_3 d\pi_{23m}^f + \beta_4 y_{1m}^f + \beta_5 NT_m + \beta_6 UN_m + \beta_7 S_m + \beta_8 crisis_m + \beta_9 pc_m + e_m, \tag{11}$$

where NT_m and UN_m are defined as outlined in 3.3.

Finally, the degree of optimism and uncertainty expressed by the SNB in their monetary policy statements might vary by topic. In order to investigate whether stock investors' uncertainty responds differently to topic-tone associations, the topic-tone scores replace NT_m and UN_m such that

$$CAV_m^D = \alpha + \boldsymbol{\beta_j} \mathbf{X_m} + \sum_{k=1}^{K} \beta_{j+k} NTS_m^k + e_m, \tag{12}$$

$$CAV_m^D = \alpha + \boldsymbol{\beta_j} \mathbf{X_m} + \sum_{k=1}^{K} \beta_{j+k} US_m^k + e_m, \tag{13}$$

where the matrix $\mathbf{X_m}$ contains all remaining variables from (11) and NTS_m^k and US_m^k are defined as described in 3.3. Although LDA is performed with $K = 8$ topics, only five of these topics are used for the regression analysis (see results in the next section).

4 Results

In this section, I present the results produced by the LDA algorithm. The algorithm provides words-to-topics associations, i.e. the most frequent words assigned to each topic. Additionally, I illustrate how the topic-tone scores vary over time. Second, the evolution of abnormal variance (CAV_m^1) on PE days over time is presented. Third, results of regressing CAV_m^D on monetary policy news are discussed.

4.1 Words-to-topics association

The LDA algorithm assigns each word w to each of the predefined number of $K = 8$ topics but with different probabilities. Table 1 displays the twelve most frequent (stemmed) words in each of the eight topics. The most frequent words are listed at the top of the table. Topic 1

Table 1: The twelve most frequent words in each of the $K = 8$ topics

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
1	monetari	forecast	franc	quarter	price	economi	growth	market
2	polici	inflat	rate	demand	inflat	econom	expect	rate
3	month	quarter	exchang	growth	term	risk	economi	interest
4	three	three	interest	export	oil	global	will	will
5	libor	new	will	continu	increas	develop	econom	financi
6	rang	remain	monetari	first	level	area	year	bank
7	target	libor	foreign	invest	rise	outlook	like	mortgag
8	rate	base	minimum	econom	effect	financi	continu	real
9	point	show	euro	labour	stabil	uncertainti	howev	lend
10	time	month	negat	increas	year	euro	recoveri	loan
11	expansionari	slight	currenc	domest	rate	market	global	money
12	decis	will	take	real	declin	situat	develop	liquid

Notes: The table displays stemmed words, which are the input to the LDA procedure.

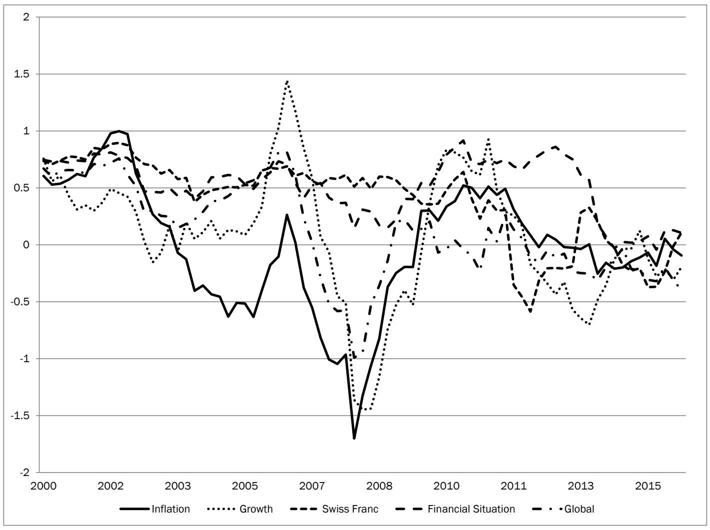
comprises words like *monetary*, *policy*, *libor*, *range*, and *decision*. Topic 1 therefore reflects the SNB's monetary **policy decision**. In contrast, in Topic 4 the most frequent words are demand, growth, export, real, and domestic indicating that it is a **growth**-related topic. I interpret the remaining topics according to their most frequent words as follows:

Topic 2: Inflation Forecast
Topic 3: Swiss Franc
Topic 5: Inflation
Topic 6: Global Environment
Topic 7: Growth
Topic 8: Financial Situation

It is remarkable that the LDA algorithm discloses the multiple dimensions of SNB communication and policy in such a clear manner. In order to reduce this dimensionality, I group **inflation**-related topics (Topic 2 and 5) as well as **growth**-related topics (Topic 4 and 7) together. This results in six major topics. Four of these reflect the SNB's mandates, i.e. **Policy**, **Inflation**, **Growth** and the **Swiss Franc** exchange rate. Additionally the topics **Global Environment** and **Financial Situation** cover the preconditions. For the regression analysis, all but the **Policy** topic are used. SNB monetary policy decisions are captured by unexpected policy rate changes (See 3.2).
The topics are used to calculate topic-tone scores for each SNB statement. The time variation of the 8-period moving average of these scores is displayed in Figure 1. Scores are standardized to zero mean and unit variance. The figure shows substantial differences between the scores over time. First, the scores related to growth and inflation show some cyclicyal pattern, becoming

more positive in economic upturns and decreasing at the onset of the financial crisis beginning 2007. The score related to the global environment shows a similar pattern. In contrast, the

Figure 1: Nettone scores over time



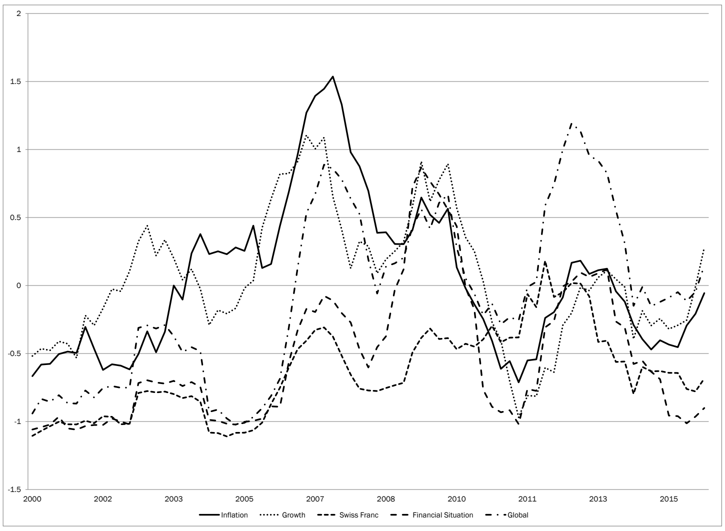
Notes: The figure plots the 8-period moving average of nettone scores on all 84 PE days. Scores are standardized to zero mean and unit variance.

Swiss Franc score does not detoriate during the crisis but decreases during the Euro crisis when the SNB was concerend about the upward pressure of the Swiss Franc and set the minimum exchange rate to the Euro. The score related to the financial situation remains unaffected by the crisis period as well. Thus, the SNB did not report major changes in Swiss financial market conditions during the crisis. This is consistent with the finding that Switzerland has been rather resilient to the shock of the 2007 to 2009 financial crisis. In contrast, the uncertainty scores show some different pattern (Figure 2). For the inflation, growth and global environment topics, uncertainty becomes more pronounced during the financial crisis and the subsequent Euro crisis. The patterns are, however, less distinct than in the case of the nettone scores. This finding suggests that the SNB expresses uncertainty more broadly across topics compared to the degree of optimism, which is more distinct by topic.

4.2 Stock market uncertainty over time

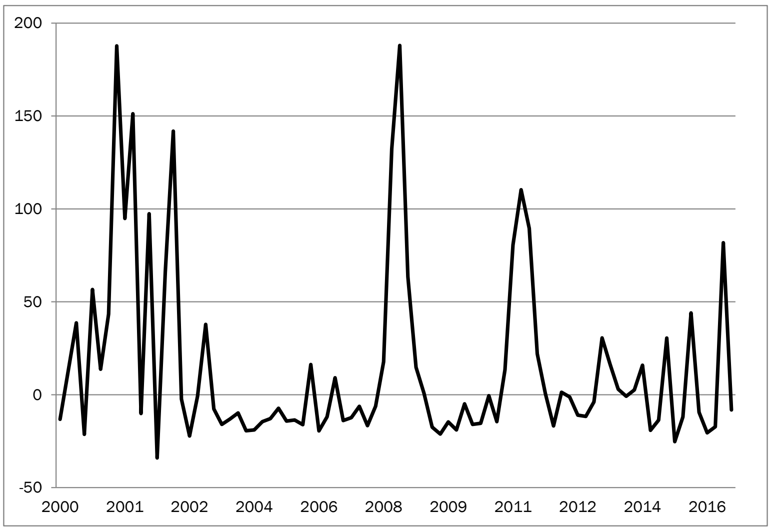
As outlined in 3.1, uncertainty is measured as the difference between monthly realized and expected stock market variance (both expressed in monthly percentages squared). In other words, uncertainty reflects the unexpected part of stock market variance. Figure 3 presents uncertainty on all 84 PE days. Values below zero indicate that realized variance was lower than expected. Uncertainty is especially high (1) at the beginning of the sample between 2000 and

Figure 2: Uncertainty scores over time



Notes: The figure plots the 8-period moving average of uncertainty scores on all 84 PE days. Scores are standardized to zero mean and unit variance.

Figure 3: Stock market uncertainty on PE days over time



Notes: The figure depicts cumulative abnormal variance (CAV_m^1) on all 84 PE days (in monthly percentages squared).

the end of 2002, (2) during the peak of the financial crisis in 2008 and (3) at the start of the minimum exchange rate to the Euro in 2011. The high uncertainty on PE days between 2000 and 2002 might also be caused by the relative frequent unscheduled PE meetings during this time interval. In contrast, uncertainty is remarkably low between 2002 and 2007.

4.3 Regression results

In order to show the effects of SNB monetary policy news on stock investors' uncertainty, this section proceeds as follows: First, estimating (10) serves as the benchmark regression. Second, the asymmetric response (good news versus bad news) to the variables $\Delta\tilde{r}^u_m$, $slope_m$ and S_m is evaluated. Third, $slope_m$ is replaced by policy news extracted from SNB statements, namely the forecasts and the statement-level nettone and uncertainty. Finally, the constructed nettone scores and uncertainty scores are added to analyze whether the nettone and uncertainty of certain topics drive changes in stock investors' uncertainty.

Results estimating (10) are given in Table 2. Cumulative abnormal variance of two to ten days responds positively to changes in $\Delta\tilde{r}^u_m$ on scheduled PE. More specifically, a (hypothetical) unexpected policy rate cut of one percentage point reduces monthly variance by 7.17 percentages squared after three trading days (CAV^3_m). This finding is consistent with the finding of the high-frequency analysis in Bekaert et al. (2013). Lax monetary policy decreases stock investors' uncertainty. The variable $slope_m$, as a proxy for changes in SNB communication, however, does affect uncertainty significantly only for the full sample after ten trading days (CAV^{10}_m). Here, a positive slope surprise, i.e. SNB communication indicating a positive outlook and future policy rate increases, reduces uncertainty. Economic news surprises affect uncertainty positively on SNB PE. This result seems to be a bit odd but might be related to the simple fact that news surprises increase variance since news must be priced in. An investigation of an asymmetric response of economic news surprises, however, gives a clearer picture of the link between news surprises and stock market uncertainty (see below). As it might be expected, uncertainty is

Table 2: Estimation of specification given in (10)

	All PE						Scheduled PE					
	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m
$\Delta\tilde{r}^u_m$	0.54	1.53	2.27	3.49	5.01	14.00*	1.88	5.31**	7.17**	9.12**	10.98**	20.86*
	(0.71)	(1.50)	(2.14)	(2.91)	(3.81)	(7.82)	(1.35)	(2.60)	(2.99)	(3.84)	(4.91)	(11.21)
$slope_m$	-0.92	-2.36	-4.22	-6.56	-9.24	-24.01**	-0.61	-1.86	-2.32	-2.95	-3.79	-10.21
	(1.26)	(2.48)	(3.55)	(4.70)	(5.90)	(11.98)	(1.41)	(2.57)	(3.19)	(4.02)	(4.94)	(10.25)
us_m	0.61***	1.27***	1.97***	2.73***	3.54***	7.81***						
	(0.20)	(0.42)	(0.64)	(0.88)	(1.13)	(2.35)						
S_m	0.13**	0.32**	0.53***	0.76***	1.00***	2.26***	0.10	0.19	0.28	0.39	0.49	1.00
	(0.06)	(0.13)	(0.18)	(0.24)	(0.31)	(0.62)	(0.09)	(0.19)	(0.28)	(0.36)	(0.44)	(0.87)
$crisis_m$	0.06	0.15	0.33	0.48	0.64	0.87	-0.10*	-0.14	-0.16	-0.18	-0.18	-0.18
	(0.11)	(0.23)	(0.37)	(0.52)	(0.67)	(1.29)	(0.06)	(0.13)	(0.20)	(0.27)	(0.34)	(0.71)
pc_m	-0.14	-0.34*	-0.61***	-0.88***	-1.15***	-2.26***	-0.10	-0.27*	-0.51**	-0.76***	-1.01***	-2.02***
	(0.09)	(0.17)	(0.23)	(0.30)	(0.36)	(0.72)	(0.08)	(0.15)	(0.20)	(0.26)	(0.33)	(0.66)
Constant	0.09	0.22	0.33	0.43	0.53	1.07	0.10	0.24*	0.38*	0.51*	0.63*	1.17*
	(0.06)	(0.13)	(0.21)	(0.28)	(0.35)	(0.68)	(0.06)	(0.13)	(0.19)	(0.26)	(0.32)	(0.63)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.27	0.29	0.35	0.38	0.39	0.45	0.15	0.24	0.29	0.31	0.31	0.30

Notes: Dependent variables are CAV^D_m for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

significantly higher on as well as after unscheduled PE. Mostly, unscheduled PE occur in times of financial distress or strong upward pressure of the Swiss franc, i.e. an unpleasant reason for the PE. In contrast, pc_m reduces uncertainty indicating the additional benefit of clarifying explanations and a Q&A of a press conference (See Ehrmann and Fratzscher 2009).

Results from testing an asymmetric response of policy rate, slope, and economic news surprises are reported in Table 3. The dummy variable P_{im} is equal to one if the corresponding variable indicates a positive surprise and zero otherwise ($i = 1$ for $\Delta\tilde{r}^u_m$, $i = 2$ for $slope_m$, $i = 3$ for S_m). In this case, uncertainty only responds significantly to changes in $\Delta\tilde{r}^u_m$ if they are positive. Therefore, unexpected contractionary policy increases stock investors' uncertainty. This includes the case where the policy rate change was less expansionary than expected. Moreover, negative slope surprises, indicating expected future policy easing, lead to reduced uncertainty of stock market investors (at least for the full sample). This finding highlights the importance of communication beyond policy rate changes in reducing noise in financial markets. Uncertainty also exhibits an asymmetric response to economic news surprises. While positive news surprises reduce uncertainty, negative news surprises increase uncertainty although the latter statistically less significantly. The last finding highlights the importance of distinguishing between "good" versus "bad" news when investigating the reaction of market uncertainty to news surprises.

Table 3: Asymmetric response of stock market uncertainty

	All PE						Scheduled PE					
	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m
P_{1m}	-0.06	-0.19	-0.31	-0.49	-0.72	-1.85*	0.01	-0.04	-0.04	-0.07	-0.13	-0.47
	(0.09)	(0.17)	(0.25)	(0.35)	(0.45)	(0.95)	(0.09)	(0.16)	(0.20)	(0.27)	(0.33)	(0.70)
$\Delta\tilde{r}^u_m$	0.24	0.29	1.08	2.69	4.88	16.89*	-0.74	-1.65	-2.55	-3.21	-3.83	-4.95
	(0.74)	(1.54)	(2.42)	(3.43)	(4.57)	(8.74)	(0.93)	(1.82)	(2.66)	(3.60)	(4.65)	(10.81)
$P_{1m} * \Delta\tilde{r}^u_m$	2.31	7.70	9.48*	10.58	11.03	11.25	4.71	12.99**	18.04***	23.09***	28.16***	51.36***
	(2.77)	(4.88)	(5.31)	(7.03)	(9.39)	(22.51)	(3.14)	(5.15)	(3.97)	(3.96)	(5.03)	(15.50)
P_{2m}	0.19	0.33	0.48	0.64	0.78	0.91	0.29***	0.55***	0.76***	0.97***	1.13**	1.64*
	(0.12)	(0.25)	(0.36)	(0.47)	(0.59)	(1.09)	(0.10)	(0.19)	(0.27)	(0.35)	(0.44)	(0.88)
$slope_m$	-3.75**	-7.63***	-10.69***	-14.08***	-17.48***	-35.67**	-3.28	-6.11	-7.33	-8.65	-9.88	-14.26
	(1.47)	(2.67)	(3.75)	(4.97)	(6.35)	(13.73)	(2.86)	(4.59)	(5.40)	(6.51)	(7.76)	(17.01)
$P_{2m} * slope_m$	3.10	6.33	6.83	7.13	7.51	20.01	-1.60	-4.53	-8.54	-12.42	-15.52	-30.69
	(4.61)	(9.31)	(13.59)	(17.86)	(22.24)	(42.06)	(3.91)	(7.03)	(9.08)	(11.56)	(14.34)	(30.23)
us_m	0.51**	0.96*	1.62**	2.36**	3.19**	7.46***						
	(0.23)	(0.49)	(0.76)	(1.05)	(1.35)	(2.75)						
P_{3m}	0.05	0.12	0.25	0.37	0.45	0.57	0.03	0.08	0.17	0.26	0.33	0.47
	(0.10)	(0.19)	(0.29)	(0.39)	(0.50)	(0.99)	(0.07)	(0.14)	(0.21)	(0.28)	(0.35)	(0.72)
S_m	0.11	0.24	0.44*	0.67**	0.94**	2.47***	0.13*	0.21*	0.29*	0.37*	0.47*	1.24**
	(0.07)	(0.15)	(0.23)	(0.31)	(0.40)	(0.80)	(0.07)	(0.12)	(0.16)	(0.20)	(0.25)	(0.53)
$P_{3m} * S_m$	-0.64**	-1.27**	-2.09**	-2.95**	-3.79***	-7.28***	-0.56**	-1.05**	-1.56**	-2.05**	-2.47**	-4.78**
	(0.27)	(0.54)	(0.84)	(1.14)	(1.43)	(2.60)	(0.23)	(0.44)	(0.63)	(0.83)	(1.02)	(1.98)
$crisis_m$	0.06	0.15	0.34	0.52	0.71	1.12	-0.08	-0.09	-0.09	-0.08	-0.06	0.05
	(0.12)	(0.24)	(0.40)	(0.55)	(0.71)	(1.36)	(0.06)	(0.12)	(0.19)	(0.26)	(0.33)	(0.73)
pc_m	-0.14*	-0.33**	-0.59***	-0.85***	-1.09***	-2.13***	-0.10	-0.27**	-0.51***	-0.76***	-1.00***	-1.99***
	(0.08)	(0.15)	(0.20)	(0.26)	(0.33)	(0.71)	(0.07)	(0.13)	(0.17)	(0.21)	(0.27)	(0.57)
Constant	-0.04	-0.06	-0.03	0.04	0.16	1.05	-0.10	-0.18	-0.21	-0.24	-0.24	-0.01
	(0.09)	(0.19)	(0.27)	(0.37)	(0.47)	(0.96)	(0.08)	(0.16)	(0.23)	(0.30)	(0.38)	(0.84)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.34	0.38	0.42	0.44	0.45	0.49	0.32	0.46	0.53	0.55	0.54	0.49

Notes: Dependent variables are CAV^D_m for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

As a next step, $slope$ is replaced by monetary policy news from SNB statements. Forecasts π^f_{1m}, $d\pi^f_{23m}$ and y^f_{1m} and the statement-level nettone (NT_m) and uncertainty (UN_m) are included. Results, reported in Table 4, indicate that uncertainty increases in response to positive changes in $d\pi^f_{23m}$. In other words, uncertainty increases if the SNB communicates that it does not expect to meet the inflation target of two percent in the medium term. In contrast, there is little evidence that changes in the current year inflation forecast affects stock market uncertainty. Changes in y^f_{1m} reflecting a positive outlook for economic activity in Switzerland do not affect uncertainty significantly.

The degree of optimism expressed in a statement affects uncertainty only for the case of scheduled PE. This seems reasonable considering the fact that statements of unscheduled PE are mostly differently structured and contain different information than statements on scheduled PE. Increased optimism reduces market uncertainty. In contrast, expressed uncertainty in statements increases stock markets' uncertainty on both scheduled and unscheduled PE. The results suggest that qualitative news expressed in SNB statements play a crucial role in stimulating uncertainty beyond the quantitative forecasts. These findings contrast those of Jegadeesh and Wu (2017), who find no significant effect of statement-level nettone and uncertainty on volatility. It is important to note, however, that while the authors investigate the effect of the FOMC minutes, which are released several weeks after the FOMC meetings, I investigate the effects of policy statements of the same day as the policy decision.

Table 4: Response of stock market uncertainty to SNB forecast, expressed optimism and uncertainty

	All PE						Scheduled PE					
	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m
P_{1m}	-0.18*	-0.41*	-0.61*	-0.85*	-1.12**	-2.37**	-0.09	-0.22	-0.24	-0.27	-0.32	-0.67
	(0.11)	(0.21)	(0.31)	(0.43)	(0.55)	(1.18)	(0.11)	(0.21)	(0.26)	(0.34)	(0.42)	(0.87)
$\Delta\tilde{r}^u_m$	0.28	0.36	1.34	3.16	5.55	18.07*	0.44	0.71	0.26	0.07	0.03	1.73
	(0.83)	(1.72)	(2.77)	(3.95)	(5.26)	(10.34)	(1.14)	(2.19)	(2.95)	(3.86)	(4.79)	(9.73)
$P_{1m} * \Delta\tilde{r}^u_m$	3.25	9.42*	11.23*	12.00	11.98	9.80	4.21	11.79**	15.98***	19.91***	23.71***	41.37***
	(2.98)	(5.44)	(6.21)	(8.14)	(10.62)	(23.58)	(2.76)	(4.54)	(3.82)	(4.37)	(5.59)	(15.23)
π^f_{1m}	-0.03	-0.06	-0.18	-0.31	-0.41	-0.58	-0.03	-0.05	-0.16	-0.28	-0.39*	-0.71*
	(0.07)	(0.14)	(0.19)	(0.25)	(0.33)	(0.71)	(0.07)	(0.13)	(0.14)	(0.17)	(0.21)	(0.42)
$d\pi^f_{23m}$	0.11	0.22	0.39	0.59	0.80	1.50	0.20**	0.39**	0.63***	0.89***	1.18***	2.37***
	(0.10)	(0.19)	(0.29)	(0.41)	(0.53)	(1.10)	(0.08)	(0.16)	(0.22)	(0.29)	(0.36)	(0.68)
y^f_m	0.02	0.03	0.05	0.05	0.04	-0.21	0.01	0.01	-0.01	-0.03	-0.05	-0.30
	(0.04)	(0.07)	(0.11)	(0.15)	(0.19)	(0.37)	(0.03)	(0.06)	(0.08)	(0.10)	(0.12)	(0.22)
NT_m	-0.02	-0.04	-0.05	-0.06	-0.07	-0.07	-0.05***	-0.09***	-0.12***	-0.15**	-0.18**	-0.31*
	(0.02)	(0.04)	(0.06)	(0.09)	(0.12)	(0.24)	(0.02)	(0.03)	(0.05)	(0.06)	(0.08)	(0.18)
UN_m	0.21**	0.41**	0.49**	0.53	0.58	0.82	0.16**	0.30**	0.32*	0.31	0.31	0.43
	(0.08)	(0.17)	(0.24)	(0.33)	(0.42)	(0.85)	(0.08)	(0.14)	(0.16)	(0.21)	(0.25)	(0.49)
us_m	0.54**	1.01**	1.54**	2.11**	2.75**	6.30**						
	(0.23)	(0.50)	(0.77)	(1.05)	(1.37)	(2.90)						
P_{3m}	0.09	0.21	0.41	0.59	0.76	1.19	0.01	0.06	0.21	0.36	0.48	0.83
	(0.10)	(0.21)	(0.32)	(0.44)	(0.56)	(1.14)	(0.08)	(0.16)	(0.21)	(0.28)	(0.35)	(0.72)
S_m	0.13*	0.28*	0.51**	0.78**	1.08**	2.67***	0.26***	0.45**	0.60**	0.74**	0.89**	1.79**
	(0.07)	(0.15)	(0.24)	(0.33)	(0.43)	(0.91)	(0.09)	(0.17)	(0.23)	(0.31)	(0.39)	(0.75)
$P_{3m} * S_m$	-0.51*	-1.06*	-1.88**	-2.76**	-3.62**	-7.48***	-0.45	-0.83	-1.34*	-1.82*	-2.22*	-4.42*
	(0.29)	(0.56)	(0.84)	(1.14)	(1.43)	(2.76)	(0.29)	(0.56)	(0.77)	(1.00)	(1.20)	(2.28)
$crisis_m$	-0.01	0.01	0.19	0.35	0.50	0.46	-0.13	-0.21	-0.23	-0.24	-0.26	-0.55
	(0.14)	(0.27)	(0.45)	(0.64)	(0.83)	(1.68)	(0.09)	(0.16)	(0.21)	(0.28)	(0.35)	(0.77)
pc_m	-0.06	-0.18	-0.36	-0.54*	-0.70*	-1.46*	0.00	-0.07	-0.22	-0.37*	-0.50**	-1.04*
	(0.08)	(0.16)	(0.23)	(0.31)	(0.39)	(0.83)	(0.07)	(0.13)	(0.16)	(0.20)	(0.25)	(0.53)
Constant	-0.12	-0.20	-0.02	0.29	0.66	2.52	0.00	0.02	0.27	0.59	0.94	2.56**
	(0.20)	(0.38)	(0.53)	(0.70)	(0.90)	(1.74)	(0.16)	(0.30)	(0.36)	(0.47)	(0.58)	(1.13)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.40	0.43	0.46	0.46	0.46	0.48	0.40	0.52	0.58	0.59	0.59	0.55

Notes: Dependent variables are CAV^D_m for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

The results from Table 4 indicate that statement-level nettone and uncertainty affect stocks investors' uncertainty. The findings, however, do not shed light on the question which topic the SNB addresses is responsible for stock market uncertainty to change. Table 5 presents results employing the constructed nettone scores NTS^{Infl}_m, NTS^{Growth}_m, NTS^{Franc}_m, NTS^{FSit}_m, and NTS_m^{Global}. More optimism concerning the growth topic significantly reduces uncertainty. Moreover, more positive discussions of the global environment reduce uncertainty at least after a lag of 9 days on scheduled PE. The results indicate that stock investors are more concerned about the outlook for economic activity than about inflation or financial market related topics. Results investigating the response of stock market uncertainty to the constructed uncertainty scores US_m^{Infl}, US_m^{Growth}, US_m^{Franc}, US_m^{FSit}, US_m^{Global} are provided in Table 6. In this case, there is no evidence that uncertainty expressed in SNB discussions about different topics affects stock market uncertainty. This result confirms the conjecture made before that uncertainty

Table 5: Response of stock market uncertainty to nettone scores

	All PE						Scheduled PE					
	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}
P_{1m}	-0.09	-0.25	-0.44	-0.67*	-0.94*	-2.20**	-0.02	-0.11	-0.16	-0.23	-0.31	-0.80
	(0.09)	(0.18)	(0.27)	(0.38)	(0.50)	(1.09)	(0.11)	(0.19)	(0.25)	(0.32)	(0.40)	(0.82)
$\Delta\tilde{r}_m^u$	0.39	0.59	1.51	3.24	5.57	18.19**	0.22	0.42	0.32	0.58	0.98	3.95
	(0.77)	(1.58)	(2.44)	(3.39)	(4.47)	(8.43)	(1.22)	(2.36)	(3.10)	(3.98)	(4.95)	(10.40)
$P_{1m} * \Delta\tilde{r}_m^u$	1.98	7.06	8.34	8.75	8.39	4.91	3.28	9.98*	13.37***	16.53***	19.46***	34.03**
	(3.02)	(5.48)	(6.13)	(7.85)	(10.12)	(22.52)	(3.31)	(5.57)	(4.73)	(4.78)	(5.52)	(13.53)
π_{1m}^f	-0.08	-0.16	-0.40	-0.65**	-0.88**	-1.54*	-0.06	-0.12	-0.29	-0.48**	-0.64**	-1.13**
	(0.10)	(0.19)	(0.24)	(0.32)	(0.40)	(0.82)	(0.10)	(0.18)	(0.20)	(0.23)	(0.27)	(0.51)
$d\pi_{23m}^f$	0.11	0.25	0.53*	0.86**	1.20**	2.49**	0.12	0.25	0.54*	0.85***	1.20***	2.52***
	(0.13)	(0.25)	(0.32)	(0.41)	(0.51)	(1.05)	(0.13)	(0.24)	(0.27)	(0.32)	(0.37)	(0.71)
y_m^f	0.06	0.10	0.12	0.12	0.12	-0.13	0.04	0.06	0.04	0.01	-0.02	-0.32
	(0.04)	(0.08)	(0.12)	(0.16)	(0.21)	(0.37)	(0.04)	(0.07)	(0.09)	(0.11)	(0.14)	(0.25)
NTS_m^{Infl}	1.79	2.84	2.03	0.50	-0.50	-4.34	1.35	2.19	1.91	1.12	0.89	2.26
	(1.76)	(3.35)	(4.94)	(6.55)	(8.16)	(15.23)	(1.29)	(2.46)	(3.38)	(4.43)	(5.49)	(11.46)
NTS_m^{Growth}	-2.44**	-4.27**	-5.94**	-7.70**	-9.63**	-14.25	-1.75**	-2.98*	-3.96*	-5.07*	-6.29*	-9.13
	(0.95)	(1.82)	(2.67)	(3.60)	(4.56)	(9.19)	(0.84)	(1.58)	(2.24)	(2.96)	(3.67)	(7.04)
NTS_m^{Franc}	0.33	0.26	1.07	2.69	4.17	13.57	1.78	2.69	2.83	3.45	3.47	2.38
	(2.05)	(3.92)	(5.39)	(6.97)	(8.63)	(17.08)	(2.16)	(4.15)	(5.21)	(6.33)	(7.26)	(11.71)
NTS_m^{FSit}	1.81	4.02	6.18	8.68	10.90	21.07	1.31	3.09	4.54	6.27	7.56	14.85
	(1.41)	(2.82)	(4.34)	(5.90)	(7.50)	(14.83)	(1.07)	(2.27)	(3.46)	(4.76)	(5.99)	(13.06)
NTS_m^{Global}	-0.03	-0.95	-3.60	-6.47	-9.34	-26.30	-0.36	-1.55	-4.08	-6.61*	-9.03*	-21.84**
	(1.55)	(3.09)	(4.65)	(6.33)	(8.03)	(16.07)	(1.30)	(2.51)	(3.12)	(3.91)	(4.70)	(9.40)
us_m	0.51*	0.91	1.36	1.85	2.40	5.52*						
	(0.28)	(0.57)	(0.86)	(1.16)	(1.49)	(3.10)						
P_{3m}	0.07	0.17	0.29	0.39	0.47	0.57	0.06	0.15	0.26	0.37	0.46	0.82
	(0.12)	(0.25)	(0.37)	(0.50)	(0.63)	(1.24)	(0.08)	(0.17)	(0.24)	(0.31)	(0.38)	(0.75)
S_m	0.14*	0.31*	0.54**	0.82***	1.13***	2.79***	0.20**	0.33*	0.48**	0.63**	0.79**	1.49**
	(0.07)	(0.15)	(0.23)	(0.30)	(0.39)	(0.79)	(0.09)	(0.18)	(0.24)	(0.30)	(0.37)	(0.73)
$P_{3m} * S_m$	-0.76**	-1.53**	-2.45**	-3.38**	-4.30**	-8.35***	-0.62*	-1.16*	-1.75*	-2.31*	-2.79*	-5.34*
	(0.38)	(0.72)	(1.04)	(1.36)	(1.67)	(2.90)	(0.34)	(0.67)	(0.93)	(1.20)	(1.45)	(2.78)
$crisis_m$	0.14	0.25	0.41	0.52	0.61	0.30	-0.06	-0.11	-0.18	-0.26	-0.33	-0.80
	(0.17)	(0.32)	(0.49)	(0.66)	(0.82)	(1.39)	(0.08)	(0.15)	(0.21)	(0.29)	(0.37)	(0.74)
pc_m	-0.11	-0.27	-0.47*	-0.63**	-0.79**	-1.42*	-0.05	-0.17	-0.35*	-0.52**	-0.70**	-1.42**
	(0.10)	(0.19)	(0.24)	(0.31)	(0.38)	(0.73)	(0.09)	(0.17)	(0.21)	(0.25)	(0.30)	(0.58)
Constant	0.16	0.37	0.74*	1.20**	1.71**	4.37***	0.15	0.32	0.67*	1.05**	1.48***	3.51***
	(0.19)	(0.34)	(0.43)	(0.54)	(0.67)	(1.30)	(0.17)	(0.31)	(0.36)	(0.43)	(0.52)	(1.04)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.34	0.38	0.43	0.46	0.47	0.51	0.33	0.46	0.54	0.58	0.60	0.57

Notes: Dependent variables are CAV_m^D for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

expressed in statements is not very topic-specific but rather affects stock market uncertainty on the statement-level.[11]

Overall, the results also relate to the findings in Ranaldo and Rossi (2010). While they find only modest response of stock index returns to monetary policy news, I find that uncertainty expressed

[11] Results from Table 5 and 6 investigating the response of market uncertainty to nettone scores and uncertainty scores are robust to a different choice of the number of topics K in the LDA procedure (Compare Table 9 to Table 12 in Appendix B). For $K = 7$ and $K = 9$, the effect of NTS_m^{Growth} on uncertainty becomes less significant for the days following the PE. Thus, the persistence of the effect depends on the choice of K. For $K = 7$, NTS_m^{FSit} becomes statistically significant. This result, however, is not robust to a different choice of K. Moreover, for $K = 7$ and $K = 9$, the effect of the uncertainty scores on stock investors' uncertainty do not change significantly in comparison to Table 6.

in stock market activity significantly reacts to SNB communication. The results underline the multidimensionality of the impact of monetary policy news on asset markets. While some news lead to significant responses of asset returns and "create news", other news reduces volatility and therefore "reduce noise".

Table 6: Response of stock market uncertainty to uncertainty scores

	All PE						Scheduled PE					
	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}
P_{1m}	-0.02	-0.14	-0.28	-0.46	-0.70	-1.98	0.09	0.09	0.12	0.15	0.15	-0.03
	(0.09)	(0.18)	(0.29)	(0.42)	(0.55)	(1.21)	(0.11)	(0.20)	(0.25)	(0.33)	(0.41)	(0.87)
$\Delta\tilde{r}_m^u$	0.24	0.32	1.25	3.00	5.31	17.97*	-0.88	-1.59	-2.43	-3.10	-3.64	-3.29
	(0.83)	(1.69)	(2.67)	(3.78)	(5.00)	(9.45)	(1.25)	(2.44)	(3.25)	(4.19)	(5.12)	(10.07)
$P_{1m} * \Delta\tilde{r}_m^u$	1.89	7.02	8.16	8.41	8.05	5.11	4.17	11.67**	15.74***	19.72***	23.63***	40.32**
	(2.96)	(5.36)	(6.19)	(8.22)	(10.78)	(24.07)	(3.24)	(5.44)	(4.75)	(5.17)	(6.25)	(15.17)
π_{1m}^f	-0.06	-0.10	-0.23	-0.36	-0.47	-0.64	-0.07	-0.11	-0.22	-0.34	-0.45	-0.77
	(0.08)	(0.15)	(0.21)	(0.27)	(0.35)	(0.73)	(0.07)	(0.14)	(0.18)	(0.23)	(0.28)	(0.56)
$d\pi_{23m}^f$	0.06	0.13	0.29	0.48	0.68	1.59	0.07	0.15	0.33	0.53	0.77*	1.81**
	(0.12)	(0.23)	(0.32)	(0.42)	(0.52)	(1.05)	(0.11)	(0.21)	(0.27)	(0.33)	(0.40)	(0.75)
y_m^f	0.04	0.06	0.07	0.07	0.06	-0.24	0.02	0.04	0.02	0.00	-0.03	-0.32
	(0.04)	(0.08)	(0.12)	(0.16)	(0.21)	(0.40)	(0.03)	(0.07)	(0.09)	(0.11)	(0.14)	(0.26)
US_m^{Infl}	2.42	3.42	3.29	3.44	3.47	-1.02	2.91	4.70	5.63	7.18	8.88	12.87
	(1.92)	(3.54)	(4.89)	(6.40)	(7.99)	(16.28)	(1.83)	(3.33)	(4.29)	(5.42)	(6.61)	(13.48)
US_m^{Franc}	0.94	2.64	3.78	3.60	3.68	8.29	-2.23	-3.70	-3.46	-3.96	-3.83	1.33
	(2.62)	(5.23)	(6.86)	(8.78)	(10.97)	(23.39)	(2.76)	(5.48)	(6.75)	(8.23)	(9.71)	(17.23)
US_m^{FSit}	-0.72	-1.29	-2.38	-3.44	-4.56	-11.21	0.22	0.50	-0.16	-0.98	-1.98	-9.69
	(1.34)	(2.67)	(3.98)	(5.44)	(6.97)	(14.42)	(1.25)	(2.40)	(3.23)	(4.19)	(5.18)	(10.17)
US_m^{Global}	-1.98	-3.01	-3.21	-3.00	-2.24	6.49	-1.60	-2.43	-2.82	-3.21	-3.31	-0.89
	(1.49)	(2.92)	(4.36)	(5.91)	(7.48)	(14.66)	(1.17)	(2.36)	(3.39)	(4.56)	(5.70)	(11.56)
us_m	0.57*	1.03*	1.53	2.09*	2.70*	5.90*						
	(0.30)	(0.61)	(0.92)	(1.25)	(1.60)	(3.31)						
P_{3m}	0.07	0.19	0.39	0.57	0.74	1.21	0.05	0.13	0.31	0.48	0.64*	1.19
	(0.11)	(0.23)	(0.36)	(0.48)	(0.61)	(1.23)	(0.09)	(0.17)	(0.23)	(0.30)	(0.37)	(0.74)
S_m	0.14**	0.31**	0.53**	0.79***	1.09***	2.70***	0.16**	0.26*	0.32	0.37	0.42	0.83
	(0.07)	(0.15)	(0.22)	(0.30)	(0.38)	(0.77)	(0.07)	(0.14)	(0.20)	(0.27)	(0.34)	(0.65)
$P_{3m} * S_m$	-0.53*	-1.16*	-2.04**	-2.93**	-3.79**	-7.84***	-0.32	-0.63	-1.03	-1.34	-1.57	-3.21
	(0.30)	(0.59)	(0.90)	(1.22)	(1.53)	(2.92)	(0.25)	(0.50)	(0.71)	(0.94)	(1.15)	(2.29)
$crisis_m$	0.10	0.21	0.44	0.63	0.80	0.73	-0.08	-0.13	-0.15	-0.18	-0.22	-0.62
	(0.16)	(0.31)	(0.52)	(0.73)	(0.94)	(1.83)	(0.07)	(0.14)	(0.19)	(0.25)	(0.32)	(0.66)
pc_m	-0.13	-0.31	-0.51*	-0.69*	-0.86*	-1.63	-0.08	-0.23	-0.41*	-0.59**	-0.77**	-1.45**
	(0.10)	(0.19)	(0.28)	(0.38)	(0.48)	(1.00)	(0.09)	(0.17)	(0.22)	(0.28)	(0.34)	(0.67)
Constant	0.05	0.17	0.46	0.82	1.23	3.65**	-0.00	0.03	0.23	0.44	0.68	2.16*
	(0.20)	(0.37)	(0.49)	(0.65)	(0.82)	(1.62)	(0.17)	(0.30)	(0.37)	(0.46)	(0.57)	(1.16)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.33	0.36	0.41	0.43	0.44	0.47	0.31	0.44	0.52	0.55	0.56	0.53

Notes: Dependent variables are CAV_m^D for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

4.4 Signaling or coordination channel

The finding that optimistic communication about growth, captured by increases in NTS_m^{Growth}, reduces stock investors' uncertainty is consistent with the finding that positive slope surprises reduce uncertainty (Compare Table 3). The remaining question is, whether communication in terms of positive growth prospects reduces uncertainty about macroeconomic fundamentals and changes investors' interest rate expectations (signaling channel) or it coordinates investors' expectations (coordination channel).

To test whether optimistic growth communication changes investors' interest rate expectations, i.e. whether it affects market uncertainty through the signaling channel, one-day changes of government bond yields from one to thirty years of maturity are regressed on NTS_m^{Growth} and other SNB monetary policy variables. Results for the full sample and scheduled PE are reported in Table 7.[12] To conserve space, only coefficients are reported.

As it is evident from Table 7, NTS_m^{Growth} does not affect bond yields at any maturity. Thus, there is no evidence that communications about growth change investors' interest rate expectations. This supports the hypothesis that it is rather the coordination channel through which SNB growth discussions affect stock market uncertainty. This finding is consistent with Born et al. (2014), who find that central banks' financial stability communications coordinate financial market participants' expectations rather than being perceived to signal future policy moves.

Table 7: Effect of NTS_m^{Growth} on the yield curve

	1Y	2Y	3Y	4Y	5Y	7Y	10Y	20Y	30Y
ALL PE									
$\Delta\tilde{r}_m^u$	0.85***	0.06	0.06	0.08	0.09**	0.09*	0.07	0.00	-0.04
π_{1m}^f	-0.04	-0.03**	-0.03**	-0.02**	-0.02**	-0.01	-0.00	0.01	0.01
$d\pi_{23m}^f$	0.03	0.02**	0.02**	0.02*	0.01	0.00	-0.00	-0.01	-0.00
y_m^f	0.02	0.00	0.00	0.00	0.01	0.00	-0.00	-0.01*	0.01
NTS_m^{Growth}	-0.41	0.09	0.14	0.13	0.09	0.05	0.05	0.08	0.04
us_m	-0.01	-0.05***	-0.05**	-0.03*	-0.02	-0.01	-0.01	-0.03	-0.02
S_m	0.00	-0.01	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.01
$crisis_m$	0.05	-0.03	-0.03*	-0.03**	-0.03**	-0.03**	-0.02**	-0.02	-0.03
pc_m	-0.00	0.02	0.02	0.01	0.01	0.01	0.00	0.00	0.01
Constant	-0.00	0.04***	0.04***	0.03**	0.02	0.01	0.00	0.00	-0.01
Obs.	84	84	84	84	84	84	84	84	84
R^2	0.41	0.31	0.36	0.39	0.39	0.30	0.21	0.17	0.15
Scheduled PE									
$\Delta\tilde{r}_m^u$	0.74***	-0.01	-0.03	0.00	0.04	0.06	0.03	-0.08	-0.17
π_{1m}^f	-0.01	-0.03*	-0.03**	-0.02**	-0.02**	-0.01	-0.00	0.01	0.00
$d\pi_{23m}^f$	0.02	0.03**	0.02*	0.02*	0.01	0.00	-0.01	-0.01	-0.00
y_m^f	0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.01*	0.01
NTS_m^{Growth}	-0.14	0.13	0.18	0.17	0.12	0.07	0.06	0.09	0.07
S_m	0.01	-0.01	0.00	-0.00	-0.00	0.00	0.01	0.01	-0.01
$crisis_m$	-0.02	-0.04*	-0.04**	-0.04***	-0.04***	-0.03**	-0.02*	-0.01	-0.03
pc_m	-0.00	0.02*	0.02**	0.02*	0.02*	0.01	0.00	0.01	0.02
Constant	0.01	0.04***	0.04**	0.03*	0.02	0.00	0.00	0.00	-0.01
Obs.	67	67	67	67	67	67	67	67	67
R^2	0.49	0.36	0.41	0.43	0.38	0.23	0.12	0.12	0.15

Notes: Dependent variables are the one-day changes of Swiss government bond yields from one (1Y) to thirty years (30Y) of maturity. To conserve space, standard errors robust to heteroscedasticity are not reported. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

5 Conclusion

This paper investigates the link between SNB monetary policy communication and stock market uncertainty. Policy news is extracted using changes in short- and medium-term futures prices and applying Latent Dirichlet Allocation (LDA) as well as a dictionary approach to SNB statements. Results indicate that SNB monetary policy actions and communication significantly affect uncertainty in financial markets. Interestingly, there is evidence for an asymmetric effect. While unexpected contractionary policy rate changes raise uncertainty, unexpected expansionary policy rate changes do not change market uncertainty significantly. Communication indicating a future rate cut, reduces uncertainty but communication pointing to future policy tighting does not affect stock market uncertainty. This stresses the beneficial role of communication in times of economic downturns or crises.

[12] The regressions presented in Table 7 resemble those in Hüning (2017), where the effects of SNB monetary policy rate surprises and communication on the yield curve are evaluated in more detail.

Moreover, policy news obtained from SNB statements exhibit a significant effect on stock investors' uncertainty. More specifically, optimistic communication of growth-related news significantly reduces stock market uncertainty. The results suggest that growth discussions in SNB policy statements coordinate stock investors' expectations, i.e. the coordination channel being at work. In contrast, only statement-level uncertainty expressed in SNB statements affects market uncertainty. Topic-specific uncertainty expressed in statements does not exhibit an effect on stock investors' uncertainty.
The findings might help to improve the central bank's communication design by highlighting which policy news matter to "reduce noise" in financial markets over a horizon up to 10 days after a monetary policy decision. In summary, the results suggest that a central bank interested in contributing to financial stability with its communication tool, should avoid unscheduled policy meetings, communicate its policies through press conferences and focus on growth prospects in its statements.

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Appendix A

Table A1: Results for the two-variable projection given in (1)

	Winsorized sample	Unwisorized sample
	$RVAR_t$	$RVAR_t$
$VSMI^2_{t-22}$	0.42***	0.44***
	(0.10)	(0.10)
$RVAR_{t-22}$	0.19***	0.16**
	(0.07)	(0.06)
Constant	14.99***	16.26***
	(4.27)	(5.08)
Obs.	2794	2794
R^2	0.16	0.12

Notes: Standard errors (in parantheses) are corrected for serial autocorrelation using 30 Newey and West (1987) lags. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

Appendix B

Table B1: Response of stock market uncertainty to nettone scores (LDA with $K = 7$)

	All PE						Scheduled PE					
	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m	CAV^1_m	CAV^2_m	CAV^3_m	CAV^4_m	CAV^5_m	CAV^{10}_m
P_{1m}	-0.11	-0.30*	-0.50*	-0.76**	-1.05**	-2.42**	-0.04	-0.14	-0.19	-0.26	-0.34	-0.85
	(0.09)	(0.18)	(0.26)	(0.36)	(0.48)	(1.02)	(0.11)	(0.20)	(0.26)	(0.33)	(0.41)	(0.82)
$\Delta\tilde{r}^u_m$	0.34	0.48	1.26	2.85	5.03	16.83**	0.27	0.51	0.44	0.79	1.23	4.51
	(0.76)	(1.55)	(2.33)	(3.20)	(4.20)	(7.66)	(1.23)	(2.36)	(2.99)	(3.78)	(4.60)	(9.37)
$P_{1m} * \Delta\tilde{r}^u_m$	2.33	7.65	9.12	9.76	9.67	7.36	3.50	10.25*	13.47***	16.42***	19.20***	32.60***
	(3.14)	(5.64)	(5.95)	(7.22)	(9.07)	(19.28)	(3.32)	(5.60)	(4.69)	(4.55)	(5.01)	(11.94)
π^f_{1m}	-0.06	-0.13	-0.34	-0.58**	-0.78**	-1.38*	-0.05	-0.11	-0.27	-0.46**	-0.62**	-1.13**
	(0.09)	(0.18)	(0.23)	(0.29)	(0.36)	(0.72)	(0.09)	(0.18)	(0.19)	(0.23)	(0.26)	(0.48)
$d\pi^f_{23m}$	0.12	0.26	0.56*	0.91**	1.27**	2.71**	0.13	0.27	0.56**	0.89***	1.24***	2.59***
	(0.13)	(0.24)	(0.32)	(0.41)	(0.52)	(1.06)	(0.13)	(0.23)	(0.26)	(0.30)	(0.35)	(0.65)
y^f_m	0.04	0.05	0.03	-0.00	-0.04	-0.53	0.03	0.04	0.00	-0.04	-0.08	-0.47**
	(0.04)	(0.09)	(0.12)	(0.16)	(0.19)	(0.33)	(0.04)	(0.07)	(0.08)	(0.10)	(0.12)	(0.20)
NTS^{Infl}_m	1.67	2.77	2.40	1.51	0.90	-0.92	0.96	1.39	0.71	-0.37	-1.11	-2.73
	(1.32)	(2.57)	(3.68)	(4.92)	(6.23)	(12.91)	(0.87)	(1.68)	(2.27)	(2.99)	(3.77)	(8.51)
NTS^{Growth}_m	-2.48**	-3.98*	-4.63	-5.46	-6.41	-5.30	-2.43**	-4.06*	-4.76	-5.69	-6.69	-7.55
	(1.17)	(2.33)	(3.55)	(4.87)	(6.27)	(13.14)	(1.12)	(2.19)	(3.02)	(3.93)	(4.86)	(9.21)
NTS^{Franc}_m	-1.06	-2.24	-2.27	-1.42	-0.34	7.44	0.32	-0.27	-1.59	-2.56	-3.89	-13.23
	(2.08)	(3.96)	(5.40)	(7.02)	(8.74)	(17.28)	(2.19)	(4.23)	(5.29)	(6.44)	(7.57)	(13.84)
NTS^{FSit}_m	2.83**	6.10**	8.75**	11.54**	14.09*	28.67**	1.88*	4.38**	6.58**	9.04**	11.27**	26.92**
	(1.35)	(2.68)	(4.14)	(5.61)	(7.11)	(14.15)	(1.07)	(2.14)	(3.10)	(4.14)	(5.17)	(10.75)
NTS^{Global}_m	-1.18	-3.46	-8.07	-12.96	-17.97*	-45.65**	0.02	-0.72	-3.18	-5.62	-8.10	-21.17**
	(1.78)	(3.56)	(5.67)	(7.92)	(10.17)	(20.64)	(1.50)	(2.81)	(3.31)	(4.07)	(4.90)	(9.76)
us_m	0.45	0.80	1.14	1.52	1.96	4.43						
	(0.28)	(0.57)	(0.83)	(1.12)	(1.42)	(2.91)						
P_{3m}	0.09	0.19	0.30	0.39	0.46	0.47	0.08	0.18	0.28	0.37	0.45	0.71
	(0.12)	(0.25)	(0.38)	(0.51)	(0.64)	(1.24)	(0.08)	(0.16)	(0.22)	(0.29)	(0.36)	(0.71)
S_m	0.13*	0.29*	0.52**	0.79***	1.09***	2.71***	0.16	0.26	0.40	0.55	0.69*	1.36
	(0.07)	(0.15)	(0.22)	(0.29)	(0.37)	(0.76)	(0.11)	(0.20)	(0.26)	(0.33)	(0.41)	(0.81)
$P_{3m} * S_m$	-0.77**	-1.56**	-2.50**	-3.45**	-4.38**	-8.66***	-0.58	-1.11	-1.72*	-2.28*	-2.78*	-5.56*
	(0.37)	(0.72)	(1.07)	(1.42)	(1.76)	(3.22)	(0.35)	(0.69)	(0.96)	(1.23)	(1.49)	(2.85)
$crisis_m$	0.13	0.23	0.35	0.41	0.47	-0.11	-0.05	-0.08	-0.14	-0.21	-0.27	-0.68
	(0.16)	(0.30)	(0.45)	(0.60)	(0.75)	(1.16)	(0.06)	(0.12)	(0.16)	(0.22)	(0.27)	(0.56)
pc_m	-0.13	-0.31*	-0.53**	-0.72**	-0.90**	-1.61**	-0.07	-0.21	-0.40**	-0.58**	-0.76***	-1.48***
	(0.09)	(0.17)	(0.23)	(0.29)	(0.36)	(0.72)	(0.08)	(0.15)	(0.18)	(0.22)	(0.26)	(0.52)
Constant	0.18	0.42	0.86*	1.40**	2.00***	5.16***	0.17	0.35	0.72*	1.13**	1.57***	3.72***
	(0.19)	(0.35)	(0.45)	(0.58)	(0.71)	(1.34)	(0.18)	(0.31)	(0.37)	(0.44)	(0.52)	(1.00)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.35	0.39	0.44	0.47	0.48	0.53	0.32	0.46	0.54	0.58	0.61	0.59

Notes: Dependent variables are CAV^D_m for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table B2: Response of stock market uncertainty to nettone scores (LDA with $K = 9$)

	All PE						Scheduled PE					
	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}
P_{1m}	-0.09	-0.25	-0.42*	-0.65*	-0.93*	-2.19**	-0.02	-0.10	-0.14	-0.21	-0.29	-0.75
	(0.09)	(0.17)	(0.25)	(0.36)	(0.47)	(1.03)	(0.10)	(0.18)	(0.23)	(0.29)	(0.36)	(0.75)
$\Delta\tilde{r}_m^u$	0.26	0.36	1.24	2.97	5.29	17.90**	-0.20	-0.33	-0.61	-0.48	-0.20	2.20
	(0.80)	(1.62)	(2.49)	(3.46)	(4.55)	(8.50)	(1.21)	(2.32)	(2.92)	(3.64)	(4.41)	(9.23)
$P_{1m} * \Delta\tilde{r}_m^u$	2.32	7.61	8.92	9.35	9.04	5.23	3.91	11.05*	14.59***	17.88***	20.97***	35.82***
	(3.03)	(5.48)	(6.11)	(7.85)	(10.16)	(22.54)	(3.28)	(5.50)	(4.56)	(4.51)	(5.12)	(13.18)
π_{1m}^f	-0.05	-0.10	-0.31	-0.54*	-0.74*	-1.32	-0.05	-0.10	-0.26	-0.45*	-0.62**	-1.13**
	(0.10)	(0.18)	(0.24)	(0.31)	(0.39)	(0.81)	(0.10)	(0.19)	(0.21)	(0.24)	(0.28)	(0.54)
$d\pi_{23m}^f$	0.08	0.19	0.46	0.78*	1.10**	2.38**	0.09	0.20	0.48*	0.80**	1.13***	2.44***
	(0.14)	(0.26)	(0.34)	(0.44)	(0.55)	(1.13)	(0.13)	(0.24)	(0.27)	(0.31)	(0.36)	(0.73)
y_m^f	0.06	0.10	0.11	0.12	0.12	-0.17	0.04	0.07	0.05	0.03	-0.00	-0.33
	(0.05)	(0.09)	(0.12)	(0.16)	(0.20)	(0.37)	(0.04)	(0.07)	(0.09)	(0.11)	(0.13)	(0.23)
NTS_m^{Infl}	1.68	2.69	1.65	-0.12	-1.64	-7.66	1.02	1.57	0.68	-0.71	-1.74	-5.51
	(1.62)	(3.17)	(4.45)	(5.78)	(7.14)	(14.38)	(1.36)	(2.68)	(3.56)	(4.54)	(5.58)	(12.03)
NTS_m^{Growth}	-2.88**	-5.12**	-6.99*	-9.31*	-11.75*	-15.62	-2.52**	-4.48*	-5.81*	-7.56	-9.35	-11.39
	(1.22)	(2.45)	(3.73)	(5.12)	(6.59)	(13.89)	(1.19)	(2.40)	(3.41)	(4.52)	(5.69)	(11.49)
NTS_m^{Franc}	0.24	0.29	1.20	2.84	4.34	14.15	2.02	3.37	3.98	4.87	5.12	5.93
	(1.85)	(3.59)	(4.77)	(5.99)	(7.29)	(14.70)	(1.88)	(3.75)	(4.87)	(5.93)	(6.82)	(11.56)
NTS_m^{FSit}	0.42	1.16	1.18	1.65	2.19	9.22	0.69	1.81	2.50	3.63	4.68	15.15
	(1.56)	(3.18)	(5.09)	(7.08)	(9.10)	(18.29)	(1.25)	(2.53)	(3.72)	(5.05)	(6.38)	(13.06)
NTS_m^{Global}	-0.43	-1.64	-4.24	-7.05	-9.83	-27.03*	-0.36	-1.35	-3.68	-5.93*	-8.17**	-19.25**
	(1.65)	(3.19)	(4.50)	(5.93)	(7.46)	(14.46)	(1.31)	(2.45)	(2.81)	(3.34)	(3.96)	(8.02)
us_m	0.52*	0.94	1.40	1.91	2.49	5.64*						
	(0.28)	(0.58)	(0.87)	(1.18)	(1.51)	(3.14)						
P_{3m}	0.09	0.19	0.31	0.42	0.50	0.63	0.08	0.17	0.28	0.38	0.47	0.79
	(0.12)	(0.24)	(0.36)	(0.49)	(0.62)	(1.21)	(0.08)	(0.16)	(0.23)	(0.30)	(0.37)	(0.74)
S_m	0.14*	0.30*	0.55**	0.84***	1.16***	2.84***	0.18*	0.30	0.46*	0.64*	0.80*	1.51*
	(0.08)	(0.16)	(0.23)	(0.31)	(0.40)	(0.81)	(0.10)	(0.19)	(0.25)	(0.33)	(0.40)	(0.80)
$P_{3m} * S_m$	-0.70**	-1.41**	-2.29**	-3.20**	-4.08**	-8.17***	-0.57*	-1.07*	-1.65*	-2.21*	-2.68*	-5.22*
	(0.35)	(0.67)	(0.97)	(1.27)	(1.56)	(2.81)	(0.32)	(0.62)	(0.87)	(1.12)	(1.36)	(2.61)
$crisis_m$	0.12	0.22	0.37	0.47	0.56	0.16	-0.07	-0.12	-0.20	-0.29	-0.37	-0.93
	(0.17)	(0.32)	(0.48)	(0.65)	(0.82)	(1.37)	(0.07)	(0.13)	(0.18)	(0.24)	(0.30)	(0.62)
pc_m	-0.13	-0.32*	-0.53**	-0.70**	-0.87**	-1.52*	-0.05	-0.18	-0.36*	-0.52**	-0.69**	-1.34**
	(0.10)	(0.18)	(0.25)	(0.32)	(0.39)	(0.77)	(0.09)	(0.17)	(0.21)	(0.26)	(0.30)	(0.59)
Constant	0.12	0.30	0.66	1.10*	1.60**	4.29***	0.10	0.24	0.57	0.95**	1.37***	3.40***
	(0.20)	(0.37)	(0.46)	(0.58)	(0.72)	(1.34)	(0.18)	(0.31)	(0.35)	(0.42)	(0.49)	(1.01)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.33	0.37	0.42	0.45	0.46	0.50	0.33	0.46	0.54	0.57	0.59	0.56

Notes: Dependent variables are CAV_m^D for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table B3: Response of stock market uncertainty to uncertainty scores (LDA with $K = 7$)

	All PE						Scheduled PE					
	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}
P_{1m}	-0.04	-0.18	-0.34	-0.54	-0.80	-2.08*	0.04	0.00	0.01	0.01	-0.02	-0.27
	(0.10)	(0.18)	(0.28)	(0.40)	(0.52)	(1.14)	(0.12)	(0.22)	(0.28)	(0.36)	(0.44)	(0.89)
$\Delta\tilde{r}_m^u$	0.31	0.48	1.51	3.34	5.75	18.73**	-0.26	-0.55	-1.36	-2.01	-2.46	-1.62
	(0.81)	(1.65)	(2.62)	(3.72)	(4.94)	(9.37)	(1.26)	(2.44)	(3.17)	(4.02)	(4.85)	(9.65)
$P_{1m} * \Delta\tilde{r}_m^u$	1.80	6.81	7.95	8.19	7.80	4.31	3.50	10.60*	14.80***	18.94***	22.89***	39.33***
	(3.05)	(5.50)	(6.19)	(8.01)	(10.36)	(23.15)	(3.30)	(5.54)	(4.92)	(5.23)	(6.13)	(14.54)
π_{1m}^f	-0.04	-0.06	-0.18	-0.29	-0.39	-0.60	-0.04	-0.05	-0.13	-0.23	-0.30	-0.55
	(0.07)	(0.14)	(0.20)	(0.27)	(0.34)	(0.75)	(0.07)	(0.14)	(0.17)	(0.21)	(0.25)	(0.52)
$d\pi_{23m}^f$	0.08	0.19	0.37	0.59	0.84	1.92	0.09	0.19	0.37	0.57*	0.82**	1.90**
	(0.12)	(0.23)	(0.34)	(0.45)	(0.57)	(1.16)	(0.11)	(0.21)	(0.27)	(0.33)	(0.40)	(0.74)
y_m^f	0.03	0.05	0.06	0.06	0.04	-0.25	0.01	0.02	0.01	-0.02	-0.05	-0.33
	(0.04)	(0.08)	(0.11)	(0.15)	(0.20)	(0.38)	(0.03)	(0.06)	(0.08)	(0.11)	(0.13)	(0.25)
US_m^{Infl}	-1.00	-3.22	-6.89	-10.13	-13.64*	-22.23	0.40	-0.51	-2.96	-5.28	-7.95	-15.44
	(1.91)	(3.57)	(4.76)	(6.10)	(7.48)	(14.39)	(2.07)	(3.91)	(4.90)	(6.04)	(7.19)	(14.47)
US_m^{Growth}	0.79	0.70	0.79	0.99	0.85	-4.93	1.32	2.36	4.04	6.29	8.39	13.44
	(2.01)	(3.95)	(5.93)	(8.06)	(10.24)	(20.40)	(1.75)	(3.42)	(4.88)	(6.50)	(8.10)	(15.69)
US_m^{Franc}	1.78	3.65	3.56	1.92	0.53	-1.65	0.83	2.12	3.51	3.98	5.36	15.63
	(2.90)	(5.76)	(7.85)	(10.18)	(12.75)	(27.67)	(2.66)	(5.42)	(7.06)	(8.70)	(10.31)	(20.78)
US_m^{FSit}	-1.31	-2.37	-3.77	-5.28	-6.78	-13.49	-0.60	-0.98	-1.90	-3.08	-4.40	-11.87
	(1.16)	(2.27)	(3.51)	(4.84)	(6.19)	(12.33)	(0.92)	(1.75)	(2.44)	(3.24)	(4.06)	(7.92)
US_m^{Global}	-0.17	0.88	3.20	5.93	9.38	25.77	-1.32	-1.80	-1.24	-0.45	0.89	7.08
	(1.55)	(3.20)	(4.78)	(6.48)	(8.17)	(16.54)	(1.41)	(2.88)	(3.91)	(5.04)	(6.11)	(12.03)
us_m	0.49*	0.86	1.27	1.73	2.24	5.19						
	(0.28)	(0.59)	(0.89)	(1.21)	(1.55)	(3.20)						
P_{3m}	0.08	0.19	0.38	0.56	0.73	1.17	0.07	0.17	0.34	0.51*	0.67*	1.20
	(0.11)	(0.23)	(0.35)	(0.48)	(0.61)	(1.23)	(0.08)	(0.17)	(0.22)	(0.29)	(0.36)	(0.73)
S_m	0.14**	0.31**	0.54**	0.80***	1.10***	2.74***	0.14*	0.24	0.30	0.35	0.40	0.83
	(0.07)	(0.15)	(0.22)	(0.29)	(0.37)	(0.76)	(0.08)	(0.15)	(0.20)	(0.26)	(0.33)	(0.63)
$P_{3m} * S_m$	-0.61**	-1.29**	-2.20**	-3.11**	-4.00***	-8.02***	-0.41	-0.80	-1.24	-1.60	-1.89	-3.67
	(0.29)	(0.58)	(0.88)	(1.18)	(1.49)	(2.89)	(0.28)	(0.55)	(0.78)	(1.02)	(1.24)	(2.42)
$crisis_m$	0.13	0.30	0.64	0.94	1.21	1.42	-0.09	-0.11	-0.05	0.00	0.05	-0.12
	(0.19)	(0.35)	(0.56)	(0.78)	(1.00)	(1.93)	(0.11)	(0.21)	(0.27)	(0.35)	(0.43)	(0.88)
pc_m	-0.10	-0.24	-0.40	-0.54	-0.66	-1.25	-0.08	-0.22	-0.39*	-0.55**	-0.71**	-1.32**
	(0.11)	(0.21)	(0.31)	(0.42)	(0.53)	(1.10)	(0.08)	(0.15)	(0.21)	(0.27)	(0.32)	(0.66)
Constant	0.14	0.35	0.74	1.21*	1.74**	4.46**	0.09	0.20	0.43	0.70	1.01*	2.65**
	(0.18)	(0.35)	(0.50)	(0.67)	(0.86)	(1.71)	(0.16)	(0.29)	(0.38)	(0.48)	(0.58)	(1.10)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.32	0.36	0.42	0.44	0.45	0.49	0.29	0.43	0.51	0.55	0.57	0.54

Notes: Dependent variables are CAV_m^D for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table B4: Response of stock market uncertainty to uncertainty scores (LDA with $K = 9$)

	All PE						Scheduled PE					
	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}	CAV_m^1	CAV_m^2	CAV_m^3	CAV_m^4	CAV_m^5	CAV_m^{10}
P_{1m}	-0.04	-0.19	-0.37	-0.58	-0.86	-2.24*	0.05	0.02	0.02	0.01	-0.04	-0.37
	(0.10)	(0.19)	(0.28)	(0.40)	(0.52)	(1.15)	(0.12)	(0.22)	(0.28)	(0.36)	(0.44)	(0.88)
$\Delta\tilde{r}_m^u$	0.30	0.43	1.40	3.19	5.55	18.39*	-0.45	-1.05	-2.09	-2.82	-3.43	-3.61
	(0.81)	(1.68)	(2.69)	(3.84)	(5.10)	(9.65)	(1.31)	(2.50)	(3.18)	(3.99)	(4.79)	(9.70)
$P_{1m} * \Delta\tilde{r}_m^u$	1.87	7.01	8.28	8.67	8.44	5.77	3.80	11.35**	15.92***	20.28***	24.55***	42.60***
	(3.02)	(5.41)	(6.12)	(8.03)	(10.48)	(23.75)	(3.36)	(5.59)	(4.84)	(4.99)	(5.75)	(13.91)
π_{1m}^f	-0.03	-0.04	-0.15	-0.27	-0.35	-0.55	-0.03	-0.03	-0.12	-0.20	-0.28	-0.54
	(0.07)	(0.15)	(0.21)	(0.28)	(0.36)	(0.80)	(0.07)	(0.13)	(0.16)	(0.20)	(0.24)	(0.52)
$d\pi_{23m}^f$	0.06	0.15	0.31	0.50	0.72	1.69	0.07	0.15	0.32	0.51	0.74*	1.79**
	(0.12)	(0.22)	(0.32)	(0.43)	(0.55)	(1.13)	(0.11)	(0.20)	(0.25)	(0.31)	(0.37)	(0.72)
y_m^f	0.03	0.05	0.06	0.06	0.05	-0.25	0.02	0.03	0.02	0.00	-0.03	-0.31
	(0.04)	(0.08)	(0.11)	(0.15)	(0.20)	(0.38)	(0.03)	(0.06)	(0.08)	(0.10)	(0.13)	(0.23)
US_m^{Infl}	-1.93	-4.93	-8.53*	-11.56*	-14.68*	-21.84	-1.00	-3.23	-6.15	-8.83	-11.86	-21.35
	(1.60)	(3.20)	(4.60)	(6.17)	(7.80)	(15.83)	(2.10)	(4.25)	(5.47)	(6.71)	(7.91)	(15.74)
US_m^{Growth}	2.98	5.39	8.82	12.47	15.62	21.18	3.40	6.84	11.88	17.49*	22.71*	34.83
	(3.28)	(6.49)	(9.45)	(12.67)	(16.04)	(32.78)	(2.89)	(5.68)	(7.91)	(10.34)	(12.82)	(26.19)
US_m^{Franc}	2.38	5.11	6.38	6.58	6.78	8.17	-0.58	-0.70	0.18	0.73	1.77	7.53
	(2.07)	(4.19)	(5.78)	(7.72)	(9.99)	(22.55)	(1.98)	(4.15)	(5.58)	(7.13)	(8.64)	(16.15)
US_m^{FSit}	-1.89	-3.67	-6.82	-10.02*	-13.12*	-25.18	-0.60	-1.21	-3.14	-5.40	-7.78	-19.11**
	(1.40)	(2.76)	(4.31)	(5.98)	(7.64)	(15.15)	(1.16)	(2.27)	(2.99)	(3.88)	(4.78)	(9.23)
US_m^{Global}	-1.10	-1.04	0.63	2.58	5.24	19.80	-0.96	-0.98	-0.19	0.63	2.09	10.00
	(1.46)	(2.98)	(4.46)	(6.09)	(7.72)	(16.00)	(1.51)	(3.16)	(4.36)	(5.61)	(6.84)	(13.66)
us_m	0.48	0.84	1.30	1.82	2.39	5.57*						
	(0.29)	(0.60)	(0.91)	(1.23)	(1.58)	(3.29)						
P_{3m}	0.07	0.17	0.34	0.51	0.65	1.04	0.05	0.13	0.28	0.44	0.58*	1.06
	(0.11)	(0.23)	(0.35)	(0.48)	(0.60)	(1.23)	(0.08)	(0.16)	(0.21)	(0.27)	(0.34)	(0.70)
S_m	0.15**	0.31**	0.54**	0.81***	1.10***	2.74***	0.16**	0.27*	0.34*	0.39	0.44	0.91
	(0.07)	(0.14)	(0.22)	(0.29)	(0.37)	(0.77)	(0.08)	(0.14)	(0.19)	(0.25)	(0.31)	(0.60)
$P_{3m} * S_m$	-0.60**	-1.27**	-2.11**	-2.95**	-3.78**	-7.62***	-0.39	-0.74	-1.11	-1.39	-1.63	-3.38
	(0.29)	(0.57)	(0.87)	(1.18)	(1.48)	(2.83)	(0.23)	(0.47)	(0.67)	(0.88)	(1.08)	(2.13)
$crisis_m$	0.18	0.37	0.72	1.01	1.28	1.48	-0.04	-0.02	0.05	0.12	0.18	0.17
	(0.19)	(0.36)	(0.58)	(0.81)	(1.04)	(1.97)	(0.09)	(0.19)	(0.25)	(0.33)	(0.40)	(0.81)
pc_m	-0.13	-0.31	-0.51	-0.69	-0.86	-1.59	-0.09	-0.24	-0.46*	-0.66**	-0.86**	-1.56**
	(0.12)	(0.22)	(0.32)	(0.43)	(0.54)	(1.15)	(0.10)	(0.18)	(0.23)	(0.29)	(0.35)	(0.73)
Constant	0.16	0.36	0.71	1.12*	1.58**	4.08**	0.08	0.19	0.40	0.65	0.95*	2.68**
	(0.17)	(0.33)	(0.46)	(0.62)	(0.78)	(1.60)	(0.16)	(0.28)	(0.35)	(0.44)	(0.53)	(1.07)
Obs.	84	84	84	84	84	84	67	67	67	67	67	67
R^2	0.33	0.37	0.43	0.45	0.46	0.49	0.30	0.44	0.54	0.58	0.60	0.56

Notes: Dependent variables are CAV_m^D for $D = \{1, 2, 3, 4, 5, 10\}$. Standard errors (in parantheses) are robust to heteroscedasticity. * indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.

Appendix C

Latent Dirichlet Allocation (LDA)

In the following, I describe the underlying statistical process of the LDA algorithm. The description is based on Jegadeesh and Wu (2017). Details and further discussions can be found in the original article of Blei et al. (2003). The dataset consists of the SNB monetary policy statements $m = 1, 2, ..., 84$, which are split into $p = 1, 2, ..., 1068$ paragraphs. LDA assumes that each of the p paragraphs contains a mixture of k topics, where θ_p^k denotes the probability that paragraph p is about topic k and the vector $\theta_p = [\theta_p^1, ..., \theta_p^K]'$ characterizes the true topic mixture of p. Furthermore, it is assumed that

$$\theta_p \sim Dirichlet_K(\mu), \tag{14}$$

where μ is a parameter vector of size k. Thus, topic mixtures are assumed to follow a Dirichlet distribution of order K. Let $Z_{p,w}$ be the topic assignment of word w in paragraph p. These assignments are assumed to follow a multinomial distribution

$$Z_{p,w}|\theta_p \sim Multinomial(\theta_p). \tag{15}$$

Let I_p denote all unique words in p and Z_p the topic assignments of all words w. The vector $\beta = [\beta_1, ..., \beta_K]'$ collects all topic distributions over all paragraphs and each β_k follows

$$\beta_k \sim Dirichlet_V(\phi), \tag{16}$$

where V denotes all words the SNB uses in its monetary policy communication. Conditional on the topic assignments and the topic distributions, the choice of the word $W_{p,w}$ follows

$$W_{p,w}|(\beta, Z_{p,w}) \sim Multinomial(\beta_{Z_{p,w}}), \tag{17}$$

where $\beta_{Z_{p,w}}$ denotes the word-topic assignment from the two distributions characterized before. Finally, Bayes' Rule is used to obtain the paragraph-specific topic structure:

$$P(\{\beta_k\}_{k=1}^K, \{\theta_p\}_{p=1}^P, \{Z_p\}_{p=1}^P | \{W_p\}_{p=1}^P) = \frac{P(\{\beta_k\}_{k=1}^K, \{\theta_p\}_{p=1}^P, \{Z_p\}_{p=1}^P, \{W_p\}_{p=1}^P)}{P(\{W_p\}_{p=1}^P)}. \tag{18}$$

The denominator of this posterior distribution, i.e. the marginal probability, is intractable to compute. For this reason, Gibbs sampling (Griffith and Steyvers 2004) is used to approximate the posterior distribution. For the estimation, two hyperparameters have to be set, α and δ. α is set to $\frac{5}{k}$ to obtain a concentrated topic mixture θ_p, i.e. one paragraph is assumed to consist of very few topics. Since paragraphs are relatively short and are set by the SNB to separate different discussions in their statement, this seems to be a reasonable parameter value. The parameter δ is set to 0.01 as recommend in Griffith and Steyvers (2004). For the sampling procedure,

I discard the first 4000 steps of the process (burn-in). After the burn-in, 2000 iterations are performed using every 500th iteration to prevent correlations between samples.
Employing LDA to obtain paragraph-specific topic proportions and topic-word-assignments revealing the topics the SNB discusses in its statements has the advantage to be objective compared to manual coding of the text. Furthermore, LDA allows the same word to belong to more than one topic with different probabilities, i.e. LDA belongs to the class of mixed membership models. There exist several extensions to this LDA framework such as the correlated topic model, the structured topic model or the dynamic topic model. A discussion of these extensions is given in Blei and Lafferty (2009). Most of these extensions, however, make sense in relatively large or heterogeneous corpora covering hundreds of topics or span over decades of time. For this reason, the standard LDA procedure introduced by Blei et al. (2003) is employed.

Appendix D

Example for the calculation of nettone scores

In the following, an example for the calculation of the nettone scores is given (Compare 3.3). Consider the following paragraph, which belongs to the SNB introductory statement of the PE on the 15/06/2000. It is the 11th paragraph ($p = 11$) since the beginning of the sample.

"In the first quarter of the current year, the Swiss economy grew by just over 3% in real terms. We can expect a rise in the same order in the second quarter. This vigorous development is broad based. Exports increased by around 10% year-on-year. Both the **favourable** economic development in the neighbouring countries and monetary conditions contributed to this trend. The situation on the domestic market is characterised by construction spending accelerating significantly, **strong** demand for capital goods, and continued brisk consumer spending."

First, to concentrate on words with informational content, common English stopwords such as *in*, *on* or *by* as well as numbers and punctuations are removed. Additionally, very frequent words such as *SNB* and *Swiss* as well as names such as *Thomas Jordan* are removed. All these words are highlighted in gray. All other words are stemmed and serve as the input for the LDA algorithm. The LDA algorithm estimates that growth is discussed in topic 4 and 7 (Compare Table 1). Topic 4 and 7 are grouped together. The corresponding estimated topic proportion for this paragraph is $\hat{\theta}^{k=4}_{p=11} + \hat{\theta}^{k=7}_{p=11} = 0.8$. At the same time, this paragraph contains two positive words highlighted bold ($NT_p = 2$). Thus, the nettone score

$$NTS^{Growth}_{p=11} = (\hat{\theta}^{k=4}_{p=11} + \hat{\theta}^{k=7}_{p=11}) * NT_{p=11} = 0.8 * 2 = 1.6. \tag{19}$$

As outlined in 3.3, the calculated nettone scores of each paragraph p are aggregated for each statement m according to (8). Uncertainty scores are calculated in a similar fashion.