Online Appendix

Overnight Rate and Signalling Effects of Central Bank Bills

European Economic Review

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This Online Appendix provides more information on the data sources, operational details of the SNB Bills program, a technical discussion of the event study estimator, as well as additional placebo and robustness tests.

A Data

Table A.1 — Data and sources

Name	Time stamp	Source	Links
CHF SNB Bills		SNB	www.snb.ch/en/mmr/reference/snb_bills_res/source/snb_bills_res.en.pdf and www.snb.ch/en/mmr/reference/snb_bills_new/source/snb_bills_new.en.pdf
USD SNB Bills		SNB	www.snb.ch/en/mmr/reference/snb_usd_bills_20100621/source/snb_usd_bills_20100621.en.pdf
CHF repo auctions		SNB	www.snb.ch/en/mmr/reference/repo_mb23/source/repo_mb23.en.pdf and www.snb.ch/en/iabout/stat/statrep/statpubdis/id/statpub_statmon_arch
USD repo auctions		SNB	www.snb.ch/en/mmr/reference/snb_usd_repo_results_20191002/source/snb_usd_repo_results_20191002.en.pdf
Speeches		SNB	www.snb.ch/de/ifor/media/id/media_speeches
Data releases		SECO/SFSO	Various press releases
Reverse repos and FX swaps		SNB	www.snb.ch/en/iabout/stat/statrep/statpubdis/id/statpub_statmon_arch
Government bond auctions		FFA	www.admin.ch/gov/de/start/dokumentation/medienmitteilungen.msg-id-16132.html
Treasury bill auctions		FFA	www.newsd.admin.ch/newsd/message/attachments/54842.pdf
Weekly reserves		SNB	www.snb.ch/de/iabout/stat/statrep/id/statpub_impdata
Monthly liabilities		SNB	data.snb.ch/en/topics/snb#!/cube/snbbipo
Annual bond market capitalization		SIX	www.six-group.com/exchanges/statistics/annual_statistics/2018_en.html
Stock market data	Trade close	Datastream	SMI, SPI, MSCI, EURO STOXX 50, S&P 500
Effective exchange rate	18.00 CET	Dukascopy	Own calculations. Weighted average CHF/EUR, CHF/USD, CHF/JPY, trade-weights from www.dukascopy.com/swiss/deutsch/marketwatch/historical/ and Müller (2017)
Bilateral exchange rates	18.00 CET	Dukascopy	www.dukascopy.com/swiss/deutsch/marketwatch/historical/
Swiss Average Rates (SAR)	18.15 CET	SNB	overnight and 3M, data.snb.ch/de/topics/ziredev#!/cube/zirepo
Government bond yields	17.00 CET	SIX	1Y-3Y and 7Y-10Y www.six-group.com/exchanges/indices/data_centre/bonds/sbi_history_en.html
Corporate bond yields	17.00 CET	SIX	7Y-10Y, various ratings (AAA-BBB, AAA-A, AAA-AA) www.six-group.com/exchanges/indices/data_centre/bonds/sbi_history_en.html
Yields of foreign CHF bond	17.00 CET	SIX	7Y-10Y, rating AAA-AA www.six-group.com/exchanges/indices/data_centre/bonds/sbi_history_en.html
US and euro area data	Various	FRED	Federal funds rate, 8Y zero coupon yield, EONIA
German 10Y bond yields	Unknown	SNB	data.snb.ch/de/topics/ziredev#!/cube/rendoblid/

Notes: All URLs accessed in October 2019. In case the documents are no longer available, the files are available from the authors upon request.

B Operational details, reverse repo operations and maturity of SNB Bills

SNB Bills were bought by a broad range of counterparties. Buyers either had reserve accounts at the SNB, access to the CH Repo Market, or access to the OTC Spot Market of the SIX Exchange (see SNB 2016).[37] The SNB has a relatively broad access policy to its facilities (see Kraenzlin and Nellen 2015). Reserve accounts can be held by domestic securities brokers/dealers, insurance companies, asset managers of collective investment schemes, as well as foreign banks.

SNB Bills were issued in American auctions with a variable rate tender. Each participant submitted the amount of securities he or she was willing to buy, jointly with a price. After the submission of the bids, the SNB chose the marginal price above which participants' offers were satisfied. Thereafter, participants paid the price they offered in their bids. Although SNB Bills were issued in American auctions, their marginal yield may have been influenced by the SNB's reverse repo operations. As a consequence, it is possible that the volume of SNB Bills affected the overnight rate.[38] But also, it is possible that issuing SNB Bills signalled the SNB's intent to tighten monetary policy in the future.

Reverse repo operations were conducted from January 2008 until November 2008 and between July 2010 and the end of the SNB Bills program in August 2011 (see Figure B.2). On 69 of 167 SNB Bill auction days, there was also a reverse repo operation. Reverse repo operations were held at 9.00 CET as a fixed rate tender (volume tender). That is, the yield was set by the SNB prior to the reverse repo operation. Panel (a) in Figure B.1 shows that the SNB usually allotted a volume of around 5 billion, although counterparties were willing to bid up to 80 billion at the given yield. This is in line with communication by SNB (2011), suggesting that reverse repo operations were mainly used to control the overnight rate, rather than the volume of reserves. Meanwhile, panel (b) shows that there is a strong and positive relationship between the reverse repo yield and the the SNB Bill marginal yield later on the same day.

It is therefore possible that the reverse repo operations in the morning influenced the price bids, and therefore the SNB Bill yield, in the SNB Bill auctions through a no-arbitrage condition. To illustrate, banks which were willing to invest their reserves at the SNB had two options: either invest in SNB Bills or in (a series of) overnight reverse repo operations. The two options were very close substitutes. Nonetheless, the investment via reverse repo operations carried some roll-over risk: While with SNB Bills, banks locked in the SNB Bill yield for a certain time-span, with reverse repo operations, banks

[37]SNB Bills were transferable and traded on the SIX Exchange. Parties without access to SNB's facilities could therefore purchase SNB Bills in the secondary market. In accordance with discussions with experts on the Swiss money market we believe that few trades occurred on the secondary market. Also, to the best of our knowledge, no information on SNB Bill yields on the secondary market is publicly available.

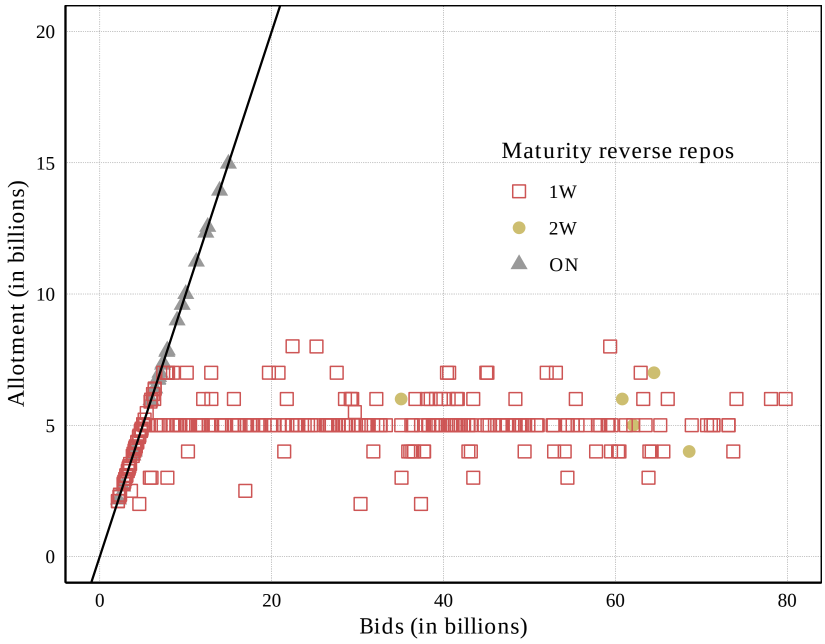
[38]Canetg and Kaufmann (2019) show in a static money market model that, for an exogenous yield on SNB Bills, increasing the volume of SNB Bills increases the demand for reserves and therefore raises the short-term interest rate. But also, reverse repo operations may have affected financial market variables if they occurred on the same day as SNB Bill auctions.

faced the risk of a falling reverse repo yield in future auctions. The uncertainty surrounding the reverse repo investment strategy likely caused the reverse repo yields to be higher than the SNB Bill yield; in contrast, the longer time to maturity in SNB Bills likely caused reverse repo yields to be lower than the SNB Bill yield.

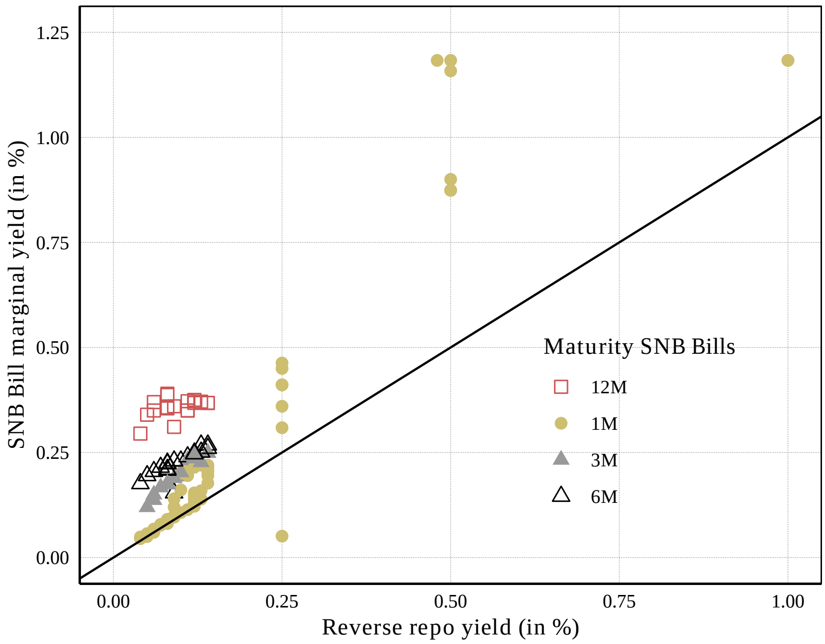
Figure B.2 shows that the maturity of SNB Bills changed significantly in the second half of the program. More bills, and bills with a longer maturity, were issued starting in mid-2010. At the same time, the SNB also conducted more reverse repo operations. we therefore examine the role of the maturity and subsamples in the main body of the text and as a robustness test, respectively. In addition, we remove reverse repo auctions in the baseline and control for the reverse repo yield and volume in a robustness test.

Figure B.1 — SNB Bills and reverse repo operations

(a) Reverse repo allotment and bids according to maturity



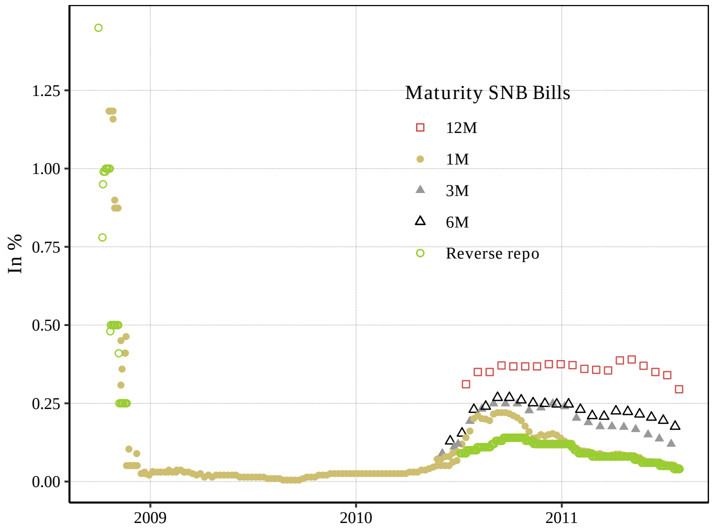
(b) Reverse repo yield and CHF SNB Bill marginal yield



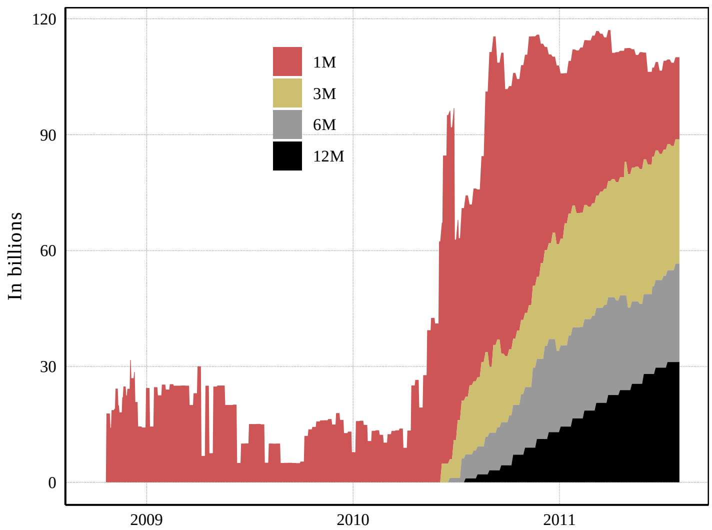
Notes: Panel (a): Bids and allotment of reverse repo auctions according to maturity during the SNB Bill program. Panel (b): CHF SNB Bill marginal yield for various maturities and reverse repo yield on the same day. 45 degree lines in black.

Figure B.2 — Yields, volume, and maturity over time

(a) CHF SNB Bill marginal yields and reverse repo yields



(b) Outstanding volume of CHF SNB Bills



Notes: Panel (a): CHF SNB Bill marginal yields for various maturities, and reverse repo yields. All reverse repos had a maturity of 2 weeks or less. Panel (b): Outstanding volume of CHF SNB Bills by maturity in buckets of approximately one month and less, three months, six months, and twelve months.

C Dynamic event study estimator

This appendix derives a dynamic event study estimator. For illustration, we assume the data is generated by a a VAR. However, we show that we can estimate the impulse response functions with local projections or a VAR. A VAR yields more precise estimates (Stock and Watson 2018), while local projections are more robust with respect to model misspecification (Jordà 2005). Plagborg-Møller and Wolf (2021) provide an equivalence result between VARs (with sufficiently long lag structure) and local projections. But the impulse responses may differ if the lag order of the VAR is too small.

Suppose that the data is generated by a VAR(1):

$$y_t = \Phi y_{t-1} + \Psi_0 e_t \ ,$$

where y_t is an N-dimensional vector of financial market variables, Φ is an $(N \times N)$ matrix of autoregressive coefficients, Ψ_0 is an $(N \times R)$ matrix of impact coefficients, and e_t is a K-dimensional vector of structural shocks.

C.1 Identification

For identification, we assume that the variance-covariance matrix of the one-step-ahead forecast errors ($e_{t|t-1}$) changes on auction days ($\Omega_{t\in A}$) compared to days without an auction ($\Omega_{t\notin A}$). Identification through heteroscedasticity exploits the difference between the two variance-covariance matrices $\tilde{\Omega} = \Omega_{t\in A} - \Omega_{t\notin A}$. This difference only depends on the responses of the N variables to K shocks occurring on auction days; meanwhile, it does not depend the $N-K$ shocks occurring on other days. For identifying the K auction day shocks we can either exploit multiple rows of $\tilde{\Omega}$ or impose additional restrictions (or combine the two).

Specifically, if we assume that there is one shock on an auction day, we can identify the model from the first row in the variance-covariance matrix (see, e.g., Nakamura and Steinsson 2018a). We need to identify N responses from one moment related to the direct effect on the policy instrument (change in variance) and $N-1$ moments related to the effect on the other $N-1$ variables (change in covariances). Therefore, the model is just identified. However, we still impose the assumption that the variance of the first variable increases on an auction day $\tilde{\Omega}_{ii} > 0$ for $i = 1$.

This does not imply, however, that using two rows of $\tilde{\Omega}$ allows us to identify two shocks. The reason is that we need to estimate $2N$ responses from only $2N-1$ independent elements of $\tilde{\Omega}$. This implies that we have to impose one additional restriction for identification. In our case, we impose a zero restriction.

More generally, suppose that we aim to identify K shocks from K rows of $\tilde{\Omega}$ in a system with N

variables. In this case we need to estimate KN responses from $KN - K(K-1)/2$ elements of $\tilde{\Omega}$. Thus, we need $(K-1)K/2$ additional restrictions.

At first sight, this implies that we can avoid the additional restrictions by exploiting more than K rows of the variance-covariance matrix. This intuition is not necessarily correct, however. Every additional row we exploit to identify an additional shock imposes the assumption that the variance of the corresponding variable i increases on an auction day ($\tilde{\Omega}_{ii} > 0$).

This discussion suggests that we can identify multiple dimensions of the shocks occurring on auction days either by imposing restrictions on how the covariance changes in response to a particular shock (e.g. a zero restriction on the response). Alternatively, we can impose that the variance of an additional variable increases on an auction day. Whether one assumption is more innocuous than the other depends on the application.

C.2 Dynamic effects

The identification strategy readily extends to dynamic causal effects. For illustration, let $\Psi_h = \Phi^h \Psi_0$ denote the impulse response after h periods from a VAR(1). We can rewrite the VAR as:

$$y_t = \Phi^{h+1} y_{t-h-1} + \Psi_h e_{t-h} + \ldots + \Psi_0 e_t \,.$$

Note y_t is determined by the h-period-ahead direct forecast, and a forecast error:

$$\begin{aligned} \mathbb{E}[y_t | y_{t-h-1}] &= \Phi^{h+1} y_{t-h-1} \\ \varepsilon_{t|t-h-1} &= \Psi_h e_{t-h} + \ldots + \Psi_0 e_t \,. \end{aligned}$$

We use that the change in the direct forecast, when one additional observation becomes available, is only caused by the structural shocks in this period. Equivalently, the change in the forecast error is only caused by the structural shocks in this period:

$$\begin{aligned} \mathbb{E}[y_t | y_{t-h-1}] - \mathbb{E}[y_t | y_{t-h}] &= \varepsilon_{t|t-h-1} - \varepsilon_{t|t-h} \\ &= \Psi_h e_{t-h} \,. \end{aligned}$$

Therefore, we can first estimate direct forecasts and forecast revisions with local projections. Second, to identify the dynamic causal effects, we can use equations (3) and (4). That is, we compare the variance-covariance of the forecast revisions, if there was an auction in period $t-h$, to the variance-covariance if there was no auction. Afterwards, we can impose sign and zero restrictions to recursively identify the effects after h periods of the two shocks.

C.3 Cumulative impulse responses

To identify the cumulative response, we can add lagged y_t to the left-hand-side of the local projection (see Stock and Watson 2018). First, note for a VAR(1), the cumulative response amounts to:

$$\Psi_0 + \Psi_1 = (I + \Phi)\Psi_0 \ ,$$

where I is a conformable identity matrix. If we add y_{t-1} on both sides of the equation of the VAR iterated one period backwards we obtain:

$$y_t + y_{t-1} = \Phi^2 y_{t-2} + \Psi_1 e_{t-1} + \Psi_0 e_t + y_{t-1} \ .$$

Replacing y_{t-1} with $\Phi y_{t-2} + \Psi_0 e_{t-1}$ yields

$$\begin{aligned} y_t + y_{t-1} &= \Phi^2 y_{t-2} + \Psi_1 e_{t-1} + \Psi_0 e_t + \Phi y_{t-2} + \Psi_0 e_{t-1} \\ &= (\Phi + \Phi^2) y_{t-2} + (\Psi_0 + \Psi_1) e_{t-1} + \Psi_0 e_t \ . \end{aligned}$$

The two-step-ahead forecast error comprises a linear combination of past (period $t-1$) and current (period t) shocks. We can remove period t shocks by subtracting the one-step-ahead forecast error.

$$\varepsilon_{t|t-2} - \varepsilon_{t|t-1} = (\Psi_0 + \Psi_1) e_{t-1}$$

and proceed as before to estimate the response.

More generally, let $\varepsilon_{t|t-h-1}$ be the $h-1$ step-ahead forecast error in

$$\sum_{j=0}^{h} y_{t-j} = \Phi^{h+1} y_{t-h-1} + \varepsilon_{t|t-h-1} \ .$$

It follows:

$$\varepsilon_{t|t-h-1} - \varepsilon_{t|t-h} = \left(\sum_{j=0}^{h} \Psi_h \right) e_{t-h} \ .$$

We can therefore estimate local projections using the cumulative sum as the dependent variable. Then, we can apply the heteroscedasticity-based identification scheme as before.

C.4 Variance decomposition

If we have estimated the impulse responses, we can compute the relative importance of the two shocks as:

$$\text{Rel. importance}_{ij} = \frac{\psi_{ij}^2}{\psi_{i1}^2 + \psi_{i2}^2} \ ,$$

which is a variance decomposition of the shock occuring on an event day into its two components. A variance decomposition to the overall variance on an event day can be similarly calculated as

$$\text{Var. decomposition}_{ij} \quad = \quad \frac{\psi_{ij}^2}{\Omega_{t\in A,ii}} \ .$$

C.5 Impulse responses using a VAR

Having computed the initial response, we can recursively compute the impulse responses using the VAR parameters (see also Wright 2012; Lütkepohl 2012; Lütkepohl et al. 2018, for similar approaches). For a VAR(1) we can compute the dynamic impact after h periods as:

$$\Psi_h = \Phi^h \Psi_0 \ .$$

To estimate the dynamic impact for a VAR(p), we can use the recursion:

$$\begin{aligned}
\Psi_1 &= \Phi_1 \Psi_0 \\
\Psi_2 &= \Phi_1 \Psi_1 + \Phi_2 \Psi_0 \\
&\vdots \\
\Psi_h &= \Phi_1 \Psi_{h-1} + \Phi_2 \Psi_{h-2} + \ldots \Phi_p \Psi_{h-p} \quad \text{for } h \geq p \ .
\end{aligned}$$

C.6 Simulations

To show under which circumstances the identification scheme works and illustrate potential pitfalls, we first simulate 1,000,000 observations from a VAR(2):

$$y_t = B^{-1}\Gamma_1 y_{t-1} + B^{-1}\Gamma_2 y_{t-2} + B^{-1} e_t \ ,$$

with

$$B^{-1} = \begin{bmatrix} 0.7 & 0.8 & 0.5 \\ 0.5 & -0.9 & 0.4 \\ 0.3 & 0.1 & 0.2 \end{bmatrix} \Gamma_1 = \begin{bmatrix} 0.3 & 0.2 & 0.4 \\ 0.7 & 0.2 & 0.5 \\ 0.1 & 0.2 & -0.4 \end{bmatrix} \Gamma_2 = \begin{bmatrix} 0.1 & 0.2 & 0.2 \\ 0.2 & 0.3 & 0.3 \\ 0.05 & 0.1 & 0.1 \end{bmatrix} E[e_t e_t'] = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

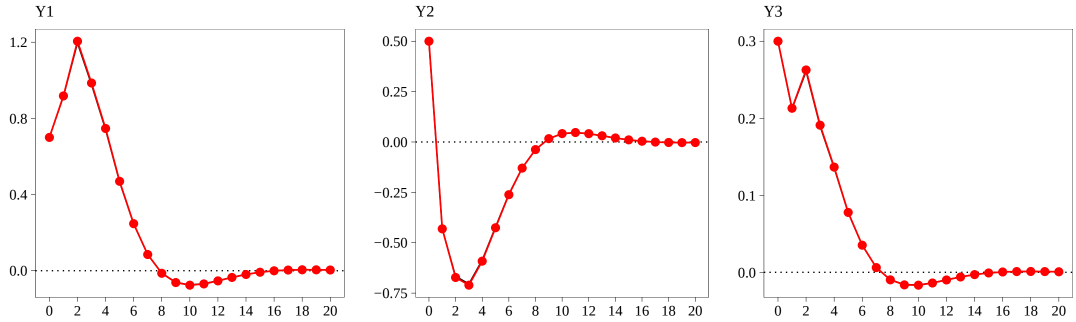
When simulating the data we impose shock 1 happens every 5th period while the other shocks occur every period. To estimate the impact of shock 1 we restrict the response of the first variable to be positive.

The black lines in Figure C.1 show the estimates of the impulse response functions.[39] The red lines are

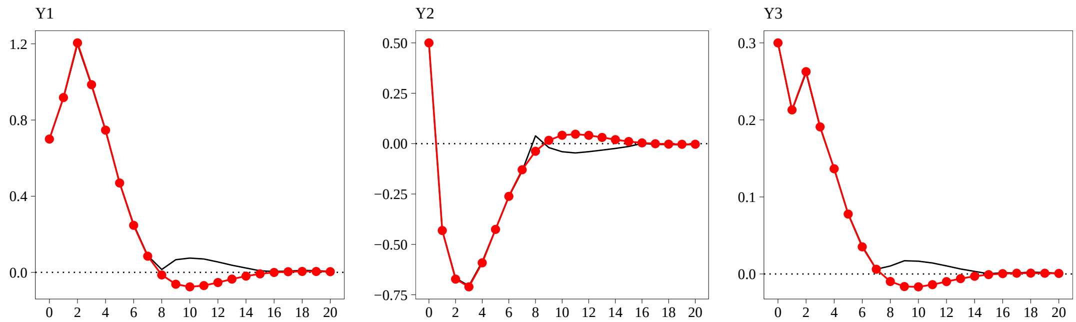
[39]We scaled the impulse response using the inverse standard deviation of structural shock 1 so that it matches the actual impulse response. In practice, as noted before, we are not able to separately identify the scale of the impulse response and the standard deviation of the structural shock.

Figure C.1 — Estimates based on 1,000,000 observations

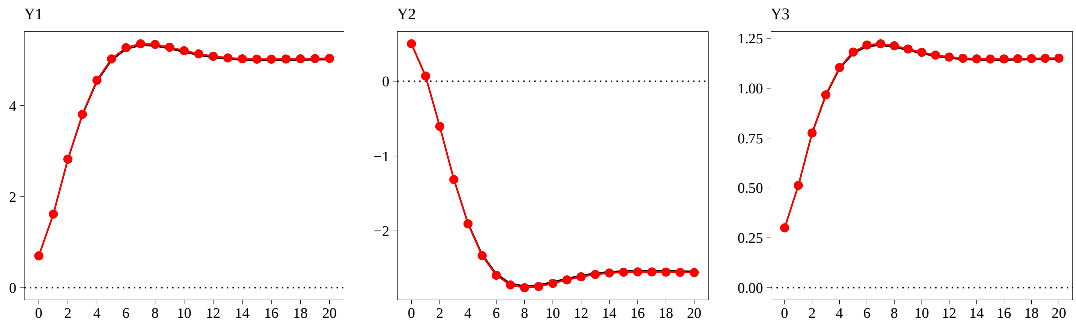
(a) VAR response



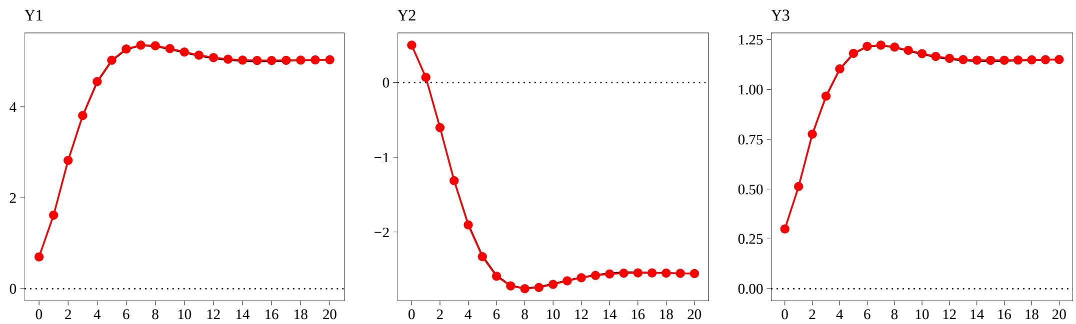
(b) Local projection response



(c) VAR cumulative response



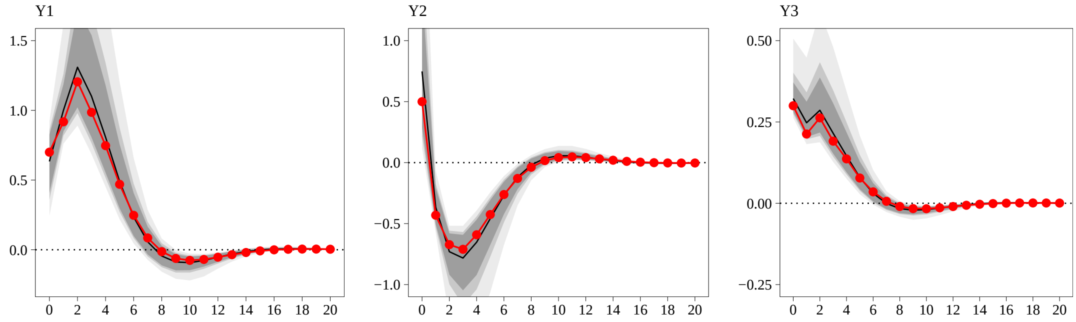
(d) Local projection cumulative response



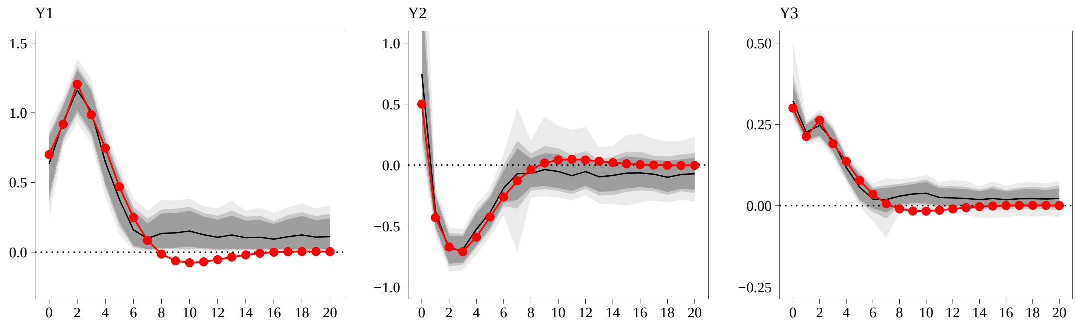
Notes: Actual response (red line with dots) and estimated response (black line).

Figure C.2 — Estimates based on 2,000 observations

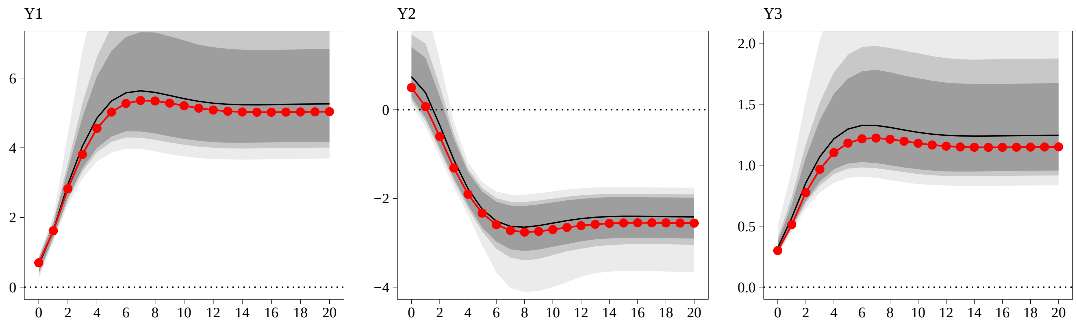
(a) VAR response



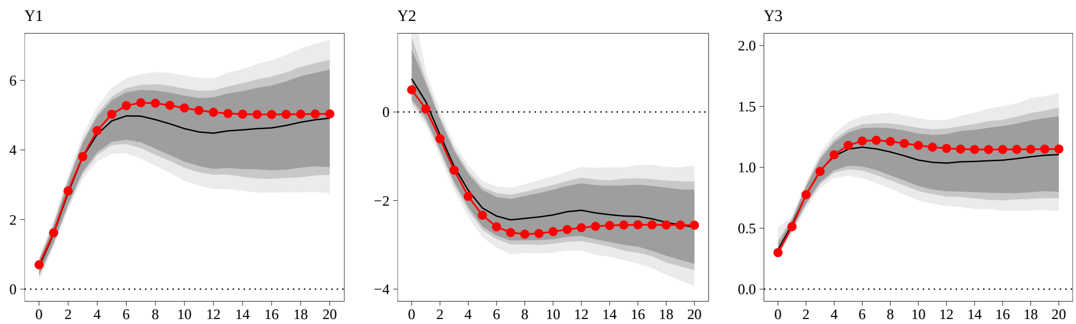
(b) Local projection response



(c) VAR cumulative response



(d) Local projection cumulative response



Notes: Actual response (red line with dots) and estimated response (black line). The shaded areas give 99%, 95%, and 90% confidence intervals based on a block bootstrap algorithm.

the actual impulse response functions. Not surprisingly, the VAR approach identifies the responses (panels a and c).

Panels (b) and (d) show the estimates using local projections. In panel (b) the identifying assumption requires the response of variable 1 is always positive. We have an identification problem when the red line crosses the zero line. Because of our identification scheme, the response of variable 1 has to remain positive, leading to a wrong sign in the responses of all other variables. Panel (d) shows we avoid this problem when identifying the response by restricting the cumulative response. Because the cumulative response of variable 1 is always positive, we also identify the responses of all other variables.

Next, we illustrate the empirical implementation of our two approaches by simulating a smaller number of observations (2,000) and estimate confidence intervals using a moving block bootstrap approach (see Efron and Tibshirani 1993, section 8.6). We set the block size to 50 and draw 5,000 bootstrap samples. Figure C.2, panel (a) shows we can estimate the impulse response using the VAR and restricting the initial response. Panel (b) shows, however, the local projections do not allow to estimate the response because of the identification problem. However, panels (c) and (d) show both approaches allow to estimate the cumulative response. Therefore, we face the following trade-off in practice. Either we choose a particular model to estimate the dynamic effects. These estimates will be precise but biased if the VAR is misspecified. Or, we use local projections which are more robust with respect to model misspecification. This comes at the cost, however, these responses are less precisely estimated and we have to impose that the shock affects stock prices at every horizon.

D Placebo and robustness tests

This appendix provides a detailed description of the placebo and robustness tests.

D.1 Placebo tests

We perform three kinds of placebo tests. First, we estimate the model on a sample from January 2005 to January 2008.[40] During this period, no SNB Bill auctions took place. Instead, we generate a placebo dummy variable with 170 random auctions occurring on either Tuesday or Thursday. We then estimate the immediate impulse responses on 200 different placebo samples. Based on these placebo estimates, we can compute various statistics. The average impact indicates whether we find the same sign and magnitude of the effect as in the actual sample. Then, we compute the share of placebo samples in which we reject the null hypothesis of no response at the 10% level. We test the null against the one-sided alternative of a drop in the SMI, an appreciation of the exchange rate, and a decline in the long-term interest rate. The share of rejections indicates how often we would falsely draw the same conclusion as in our main analysis. Finally, we compute the share of placebo samples where at least 90% of the bootstrapped impulse responses are consistent with our identifying assumption. This share indicates how often we wrongly conclude the identifying assumption is satisfied.

Table D.1 — Placebo tests: Impact of signalling shock on random auction days

(a) Random auction day before SNB Bills program (2005-2008)

	Stock prices	Exchange rate	10Y interest rate
Average impact	-0.24	-0.05	0.00
Share rejected	1.00	0.30	0.10
Share identified	0.00	0.00	0.00

(b) Random auction day during SNB Bills program

	Stock prices	Exchange rate	10Y interest rate
Average impact	-0.47	-0.12	0.01
Share rejected	1.00	0.22	0.03
Share identified	0.00	0.00	0.00

Notes: Results of two placebo simulations using 170 auction dummies generated on random days. The signalling shock is identified with sign and zero restrictions. Panel (a) uses a sample from 2005 to 2008, when no SNB Bills were issued, with random auctions occurring on Tuesdays or Wednesdays. Panel (b) uses the actual sample, when SNB Bills were issued, with random auctions occurring on days without an SNB Bill auction. We generate 200 placebo samples. The first row reports the average of the immediate impact (averaged over all bootstrap replications and placebo samples). The second row reports the share of placebo samples rejecting the null hypothesis of no response at the 10% level. We test the null against the one-sided alternative of a drop in the SMI, an appreciation of the exchange rate, and a decline in the long-term interest rate. The last row shows the share of placebo samples with at least 90% of the bootstrapped impulse responses for which $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified).

Panel (a) of Table D.1 shows the results. They suggest that there was no impact of the placebo auctions on the exchange rate. In fact, the average coefficient on the exchange rate is positive and we reject

[40] The bond yields recorded at 17.00 CET start only in early 2008. For this exercise, we therefore link them with data from the SNB available on data.snb.ch/de/topics/ziredev#!/cube/rendoblid.

the null hypothesis only in 30% of all cases. For the interest rate, we find no effect on average, and we reject the null hypothesis in 10% of all cases. Because we use a 10% significance level, and we condition on a decline in stock prices, the share of rejections appear small. To show whether the identifying assumption, a decline in stock prices, is supported by the data the last row shows the share of bootstrap samples that fulfill this restriction: This is almost never the case. Therefore we conclude, before the SNB Bills program was in place, Tuesdays and Thursdays did not systematically differ from other days.

Second, we perform a placebo test during the sample where the SNB Bills program was in place. We randomly select placebo days on which no SNB Bill auction occurred. Panel (b) shows there is some evidence that, conditional on a decline in stock prices, the Swiss franc appreciates during these random auction days. But there is virtually no effect on average on the long-term interest rate. In addition, the rejection rates are relatively small (22% and 3%). Most importantly, the identifying assumption almost never holds.

Table D.2 — Placebo tests: Effect of other events

	Signalling shock		
	Treasury bill auction	USD SNB Bill auction	Reverse repo auction
Share identified	0.35	0.04	0.01
N overall	725	725	725
N auctions	114	34	57
N without auctions	148	207	219

Notes: Impact of other events. The one standard deviation signalling shock is identified with sign and zero restrictions. We assume that it leads to a decline in stock prices but no change in the overnight interest rate. 90% and 95% confidence intervals are shown in brackets and parentheses, respectively. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the share of bootstrap replications for which $\tilde{\Omega}_{11} > 0$ or $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified), the overall number of observations to estimate the parameters (N overall), the number of observations to estimate $\Omega_{t \in A}$ (N auctions), and $\Omega_{t \notin A}$ (N without auctions). Note that N overall = N auctions + N without auctions + N other events. We remove N other events from the computation of the variance covariance matrices.

Third, we examine whether other events had an impact on financial market variables (auctions of SNB Bills in USD, treasury bill auctions, and reverse repo auctions). USD SNB Bill auctions should not affect the Swiss overnight interest rate and other financial market variables because they do not drain CHF reserves. In addition, we expect that treasury bill auctions have no impact because the SNB issues these bills on behalf of the Swiss Confederation, that is without the intention of draining CHF reserves. Finally, reverse repo operations could have a similar impact as SNB Bill auctions. As explained in Section 3, however, the volume of reverse repo operations was much smaller and the SNB argued that these operations were not intended to drain reserves.

The results are shown in Table D.2. For brevity we only show whether the identifying assumption, that there is a signalling dimension of these operations, holds. The share of bootstrap replications supporting the identifying assumption amounts only to 35% (treasury bills), 4% (USD SNB Bills) and 1% (reverse repos). Therefore, there is no convincing evidence that these operations have similar signalling effects as CHF SNB Bill auctions.

D.2 Robustness tests

In addition, we perform a range of robustness tests, mostly focusing on the signalling shock. First, we change the control variables (add lags of the dependent variables, remove foreign variables, include the yield and volume of reverse repo auctions on the same day, and clean the data from international factors). In the second to last column we add days where reverse repo operations took place. The last column shows results where we cleaned the data from international factors instead of including foreign controls. In particular, we estimate factors from a data set including US and euro area short-term rates, long-term rates, exchange rates, and stock prices. We then estimate three international factors using a principal components estimator. Finally, we regress all Swiss variables on these factors and then estimate the model on the resulting residuals.

These controls do not materially affect the results. There are two exceptions. The signalling shock is not well identified when controlling for reverse repo auctions and international factors. Adding the reverse repo controls we also add the days when reverse repo operations took place. The covariates therefore do not seem to capture the entire effect of the reverse repo auctions. Moreover, estimating the international factors and the residuals may introduce noise. This noise may then result in weaker identification due to an 'errors-in-variables' problem. We therefore prefer our better identified baseline specification.

Second, we explore alternative outcomes, that is, bilateral exchange rates (CHF/EUR, CHF/USD, and CHF/JPY) and broader stock price indices (i.e. the MSCI Switzerland and the Swiss Performance Index, SPI). In both cases, the results remain qualitatively the same. The only difference is that the effect on the CHF/JPY and the CHF/USD are less precisely estimated.

Third, we estimate the impact of a signalling shock on various spreads, that is, two different term spreads and alternative definitions of corporate bond spreads. We find that the term spreads decline in response to a signalling shock but increase in response to an overnight rate shock. The decline in response to a signalling shock is smaller and not statistically significant for the 8Y-2Y spread. In addition, the decline in the 8Y-3M spread is larger in absolute size than the long-term interest rate in the baseline specification. This suggests that the signalling shock pushed up rates at the short end of the yield curve but leads to an overall decline in long-term interest rates. In combination, this contractionary signalling shock compresses the yield curve. Finally, we find that alternative definitions of risk premia using corporate bonds with a higher rating yield similar results.

Table D.3 — Robustness tests: Controls

	Signalling shock				
	One lag	Two lags	No for. controls	Rev. repo controls	Int. factors
ON interest rate (in pp)	0.000	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
8Y interest rate (in pp)	-0.034	-0.034	-0.038	-0.016	-0.043
	[-0.058, -0.011]	[-0.058, -0.011]	[-0.054, -0.018]	[-0.046, 0.030]	[-0.085, -0.015]
	(-0.066, -0.007)	(-0.065, -0.007)	(-0.057, -0.014)	(-0.052, 0.059)	(-0.113, -0.010)
Stock prices (in %)	-0.803	-0.780	-1.348	-0.964	-0.344
	[-1.170, -0.347]	[-1.135, -0.351]	[-1.934, -0.695]	[-1.374, -0.422]	[-0.566, -0.114]
	(-1.229, -0.256)	(-1.193, -0.264)	(-2.031, -0.540)	(-1.440, -0.313)	(-0.604, -0.084)
Exchange rate (in %)	-0.336	-0.332	-0.210	-0.153	-0.273
	[-0.701, -0.066]	[-0.682, -0.062]	[-0.461, -0.007]	[-0.400, 0.074]	[-0.812, 0.182]
	(-0.883, -0.024)	(-0.849, -0.018)	(-0.552, 0.024)	(-0.492, 0.178)	(-1.103, 0.294)
Share identified	0.95	0.95	0.99	0.66	0.77
N overall	725	725	725	725	725
N auctions	52	52	52	52	52
N without auctions	207	207	207	365	207

Notes: Impact of a one standard deviation SNB Bill signalling shock identified with sign and zero restrictions. Each column shows results for a different model specification. We add one and two lags of all dependent variables, respectively. Then, we remove the foreign control variables. The third column shows results adding reverse repo auctions of the same day (volume and yield). Finally, we remove international factors by using residuals from regressing the Swiss data on the first three principal components estimated on a set of foreign financial market variables. 90% and 95% confidence intervals are shown in brackets and parentheses, respectively. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the share of bootstrap replications for which $\tilde{\Omega}_{11} > 0$ or $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified), the overall number of observations to estimate the parameters (N overall), the number of observations to estimate $\Omega_{t \in A}$ (N auctions), and $\Omega_{t \notin A}$ (N without auctions). Note that N overall = N auctions + N without auctions + N other events. We remove N other events from the computation of the variance covariance matrices.

Table D.4 — Robustness tests: Stock prices and exchange rate

	Signalling shock				
	CHF/EUR	CHF/USD	CHF/JPY	SPI	MSCI
ON interest rate (in pp)	0.000	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
8Y interest rate (in pp)	-0.033	-0.033	-0.033	-0.032	-0.032
	[-0.052, -0.012]	[-0.052, -0.012]	[-0.052, -0.012]	[-0.051, -0.012]	[-0.051, -0.012]
	(-0.057, -0.008)	(-0.057, -0.008)	(-0.057, -0.008)	(-0.056, -0.008)	(-0.055, -0.008)
Stock prices (in %)	-0.907	-0.907	-0.907	-0.835	-0.903
	[-1.326, -0.394]	[-1.326, -0.394]	[-1.326, -0.394]	[-1.221, -0.366]	[-1.319, -0.395]
	(-1.393, -0.289)	(-1.393, -0.289)	(-1.393, -0.289)	(-1.287, -0.275)	(-1.386, -0.288)
Exchange rate (in %)	-0.311	-0.416	-0.314	-0.334	-0.318
	[-0.586, -0.074]	[-1.232, 0.086]	[-1.362, 0.332]	[-0.676, -0.093]	[-0.650, -0.087]
	(-0.717, -0.027)	(-1.597, 0.145)	(-1.887, 0.404)	(-0.847, -0.054)	(-0.811, -0.050)
Share identified	0.95	0.95	0.95	0.94	0.95
N overall	725	725	725	725	725
N auctions	52	52	52	52	52
N without auctions	207	207	207	207	207

Notes: Impact of a one standard deviation SNB Bill signalling shock identified with sign and zero restrictions. Each column shows results for a different model specification. We use three bilateral exchange rates instead of the trade-weighted one (CHF/EUR, CHF/USD, CHF/JPY). Then, we use the Swiss Performance Index (SPI) and the MSCI, two broader stock price indexes than the SMI. 90% and 95% confidence intervals are shown in brackets and parentheses, respectively. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the share of bootstrap replications for which $\tilde{\Omega}_{11} > 0$ or $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified), the overall number of observations to estimate the parameters (N overall), the number of observations to estimate $\Omega_{t \in A}$ (N auctions), and $\Omega_{t \notin A}$ (N without auctions). Note that N overall = N auctions + N without auctions + N other events. We remove N other events from the computation of the variance covariance matrices.

Table D.5 — Robustness tests: Spreads

	Effects of orthogonalized shocks		Variance share explained by		
	Signalling	Overnight rate	Signalling	Overnight rate	Total
ON interest rate (in pp)	0.000	0.019	0.00	0.75	0.75
	[0.000, 0.000]	[0.013, 0.025]	[0.00, 0.00]	[0.55, 0.91]	[0.55, 0.91]
	(0.000, 0.000)	(0.012, 0.026)	(0.00, 0.00)	(0.49, 0.92)	(0.49, 0.92)
Term spread 8Y - 3M	-0.041	0.040	0.75	0.64	1.41
(in pp)	[-0.071, -0.012]	[0.001, 0.087]	[0.10, 1.49]	[0.00, 1.64]	[0.21, 2.69]
	(-0.081, -0.007)	(-0.002, 0.096)	(0.05, 1.93)	(0.00, 1.94)	(0.13, 3.33)
Term spread 8Y - 2Y	-0.012	0.005	0.36	0.07	0.43
(in pp)	[-0.038, 0.010]	[-0.008, 0.023]	[0.00, 0.97]	[0.00, 0.30]	[0.01, 1.11]
	(-0.047, 0.014)	(-0.010, 0.027)	(0.00, 1.52)	(0.00, 0.40)	(0.00, 1.63)
8Y risk premium	0.014	-0.006	0.67	0.16	0.83
A-AAA (in pp)	[0.000, 0.026]	[-0.017, 0.005]	[0.02, 1.08]	[0.00, 0.51]	[0.08, 1.33]
	(-0.003, 0.030)	(-0.019, 0.006)	(0.01, 1.53)	(0.00, 0.62)	(0.04, 1.75)
8Y risk premium	0.015	-0.003	0.85	0.09	0.94
AA-AAA (in pp)	[0.004, 0.025]	[-0.012, 0.005]	[0.06, 1.38]	[0.00, 0.31]	[0.13, 1.50]
	(0.001, 0.029)	(-0.013, 0.007)	(0.02, 2.03)	(0.00, 0.39)	(0.07, 2.10)
Share identified	0.95	1.00			
N overall	725	725			
N auctions	52	52			
N without auctions	207	207			

Notes: Responses of corporate risk premiums and term spreads to one standard deviation SNB Bill shocks identified with heteroscedasticity and zero restrictions. We assume that a signalling shock leads to a decline in stock prices but no change in the overnight interest rate. The overnight rate shock leads to an increase in the overnight interest rate. The right panel gives a variance decomposition. 90% and 95% confidence intervals are shown in brackets and parentheses, respectively. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the share of bootstrap replications for which $\tilde{\Omega}_{11} > 0$ or $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified), the overall number of observations to estimate the parameters (N overall), the number of observations to estimate $\Omega_{t \in A}$ (N auctions), and $\Omega_{t \notin A}$ (N without auctions). Note that N overall = N auctions + N without auctions + N other events. We remove N other events from the computation of the variance covariance matrices.

Fourth, we explore various subsamples. We split the sample when the 3M interest rate was above and below 25bp (before and after 19 March 2010) to examine whether we find differences when the zero lower bound was effectively binding. Shortly before, the SNB also started to view the banking system to be in a liquidity surplus (see SNB 2011). In addition, we split the sample in June 2010, when the SNB started to issue SNB Bills with a longer term to maturity. Because there are fewer auctions in the split samples, we use a broader definition of counterfactual days (including treasury bill auction days). Unfortunately, both shocks are not well identified in these different subsamples. In addition, the economic environment changed in Switzerland with respect to various dimensions at the same time (more hawkish communication, longer maturity SNB Bills, liquidity surplus). Therefore, we cannot cleanly attribute differences in the subsample analysis to particular events.

Table D.6 — Robustness tests: Subsamples

	Signalling shock			
	After March 2010	Before March 2010	After May 2010	Before May 2010
ON interest rate (in pp)	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
8Y interest rate (in pp)	0.013	-0.016	0.021	-0.014
	[-0.019, 0.069]	[-0.046, 0.016]	[-0.010, 0.076]	[-0.042, 0.021]
	(-0.037, 0.108)	(-0.057, 0.036)	(-0.018, 0.122)	(-0.051, 0.044)
Stock prices (in %)	-0.396	-0.858	-0.437	-0.824
	[-0.667, -0.132]	[-1.290, -0.352]	[-0.713, -0.135]	[-1.232, -0.332]
	(-0.702, -0.082)	(-1.351, -0.261)	(-0.774, -0.106)	(-1.301, -0.249)
Exchange rate (in %)	0.026	0.042	-0.068	-0.003
	[-0.522, 0.708]	[-0.132, 0.247]	[-0.754, 0.771]	[-0.185, 0.179]
	(-0.857, 1.296)	(-0.189, 0.345)	(-1.021, 1.396)	(-0.242, 0.245)
Share identified	0.06	0.76	0.08	0.75
N overall	355	370	303	422
N auctions	57	70	46	81
N without auctions	268	208	234	242

Notes: Impact of a one standard deviation SNB Bill signalling shock identified with sign and zero restrictions. Each column shows results for a different sample period. The first two columns show results when the 3M interest rate was below and above 25bp and the SNB judged that there was excess and scarce liquidity on money markets (before and after March 2010). The last two columns show results when the SNB started to issue long-term SNB Bills (before and after May 2010). 90% and 95% confidence intervals are shown in brackets and parentheses, respectively. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the share of bootstrap replications for which $\tilde{\Omega}_{11} > 0$ or $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified), the overall number of observations to estimate the parameters (N overall), the number of observations to estimate $\Omega_{t\in A}$ (N auctions), and $\Omega_{t\notin A}$ (N without auctions). Note that N overall = N auctions + N without auctions + N other events. We remove N other events from the computation of the variance covariance matrices.

Fifth, we examine the role of various definitions of counterfactual days. We varied the definition of days without an auction from broad—excluding only official monetary policy assessments as well as US repo and USD SNB Bill auctions—to narrow—excluding daily operations in USD, treasury and government bond auctions, foreign exchange swaps, reverse repo operations, speeches, and important data releases. For the narrow definition, we therefore have more auction days and days without an auction. The sign and magnitude of the effects are qualitatively robust for specifications excluding treasury bill auction days (column 2). However, the signalling shock is not well identified. When additionally excluding reverse repo auctions in column (4), that is our baseline specification, the signalling shock is well identified. This highlights the importance of excluding other events that may raise the counterfactual variance of financial market variables on days without an SNB Bill auction. Controlling for speeches and important data releases does not qualitatively change the results (column 5). If anything, the shock is slightly better identified.

Table D.7 — Robustness tests: Counterfactual days

	Signalling shock				
	(1)	(2)	(3)	(4)	(5)
ON interest rate (in pp)	0.000	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
8Y interest rate (in pp)	0.004	-0.017	-0.015	-0.033	-0.037
	[-0.028, 0.062]	[-0.047, 0.028]	[-0.045, 0.036]	[-0.052, -0.012]	[-0.058, -0.015]
	(-0.039, 0.112)	(-0.053, 0.064)	(-0.051, 0.079)	(-0.057, -0.008)	(-0.064, -0.010)
Stock prices (in %)	-0.753	-0.904	-0.961	-0.907	-1.049
	[-1.088, -0.380]	[-1.312, -0.374]	[-1.376, -0.415]	[-1.326, -0.394]	[-1.507, -0.489]
	(-1.130, -0.257)	(-1.383, -0.270)	(-1.442, -0.300)	(-1.393, -0.289)	(-1.572, -0.369)
Exchange rate (in %)	0.053	-0.162	-0.140	-0.320	-0.326
	[-0.123, 0.305]	[-0.434, 0.086]	[-0.386, 0.116]	[-0.653, -0.082]	[-0.652, -0.084]
	(-0.167, 0.572)	(-0.559, 0.193)	(-0.495, 0.239)	(-0.824, -0.045)	(-0.805, -0.044)
Share identified	0.20	0.68	0.67	0.95	0.97
N overall	725	725	725	725	725
N auctions	127	52	52	52	42
N without auctions	476	394	365	207	153

Notes: Impact of a one standard deviation SNB Bill signalling shock identified with sign and zero restrictions. Each column shows a different definition of days without an event. (1) excluding official monetary policy assessment of the SNB and ECB, as well as excluding USD repo and USD SNB Bills; (2) additionally excluding treasury bill and government bond auctions; (3) additionally excluding foreign exchange swap auctions; (4) additionally excluding reverse repo auctions; (5) additionally excluding speeches and data releases (Swiss CPI, PPI, GDP). 90% and 95% confidence intervals are shown in brackets and parentheses, respectively. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the share of bootstrap replications for which $\tilde{\Omega}_{11} > 0$ or $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified), the overall number of observations to estimate the parameters (N overall), the number of observations to estimate $\Omega_{t\in A}$ (N auctions), and $\Omega_{t\notin A}$ (N without auctions). Note that N overall = N auctions + N without auctions + N other events. We remove N other events from the computation of the variance covariance matrices.

Sixth, we impose alternative restrictions to identify a signalling shock. First, we may question the zero restriction on the overnight rate to disentangle the two dimensions. Second, restricting stock prices may imply a reduction of future cash flows, an increase in the riskless interest rate, or an increase in corporate risk premia. To address the first objection, the first two columns only restrict a forward-looking variable to identify a single SNB Bill shock. To address the second, the first column restricts the exchange rate to appreciate rather than stock prices to decline. Qualitatively, the results remain similar. The effects are less precisely estimated when restricting the exchange rate. Then, we identify the shock by restricting corporate risk premia, inflation expectations and the term spread. The results are not well identified, however. In particular, the results for term and corporate bond spreads highlight that the shock we identify differs from a large-scale asset purchase shock.

Table D.8 — Robustness tests: Alternative restrictions

	Signalling shock				
	Only ex. rate	Only stock prices	Risk prem.	Inflation exp.	Term spread
ON interest rate	0.001	0.000	0.000	0.000	0.000
(in pp)	[-0.005, 0.008]	[-0.009, 0.007]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
	(-0.006, 0.009)	(-0.012, 0.009)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
8Y interest rate	-0.005	-0.033	-0.057	-0.067	-0.019
(in pp)	[-0.019, 0.011]	[-0.052, -0.013]	[-0.119, -0.022]	[-0.118, -0.020]	[-0.032, -0.002]
	(-0.021, 0.015)	(-0.056, -0.008)	(-0.178, -0.017)	(-0.182, -0.015)	(-0.035, 0.004)
8Y risk premium	0.002	0.015	0.011	0.023	0.011
(in pp)	[-0.004, 0.009]	[0.003, 0.027]	[0.003, 0.019]	[-0.003, 0.056]	[-0.006, 0.024]
	(-0.005, 0.010)	(0.000, 0.030)	(0.002, 0.020)	(-0.007, 0.078)	(-0.011, 0.026)
8Y-3M term	-0.006	-0.040	-0.032	-0.046	-0.022
spread (in pp)	[-0.021, 0.011]	[-0.065, -0.014]	[-0.095, 0.037]	[-0.096, 0.012]	[-0.035, -0.008]
	(-0.023, 0.015)	(-0.070, -0.009)	(-0.130, 0.073)	(-0.131, 0.030)	(-0.036, -0.006)
Inflation expectations	-0.004	-0.018	-0.023	-0.012	-0.010
(in pp)	[-0.015, 0.008]	[-0.032, -0.004]	[-0.064, 0.004]	[-0.022, -0.004]	[-0.026, 0.006]
	(-0.017, 0.010)	(-0.037, -0.001)	(-0.098, 0.009)	(-0.023, -0.003)	(-0.032, 0.013)
Stock prices	-0.481	-0.927	-2.377	-2.413	-0.784
(in %)	[-0.786, -0.146]	[-1.340, -0.411]	[-5.401, -0.702]	[-4.881, -0.412]	[-1.368, -0.125]
	(-0.838, -0.076)	(-1.408, -0.310)	(-7.202, -0.580)	(-7.058, -0.195)	(-1.763, 0.044)
Exchange rate	-0.511	-0.308	-0.279	-0.378	-0.328
(in %)	[-0.616, -0.395]	[-0.624, -0.081]	[-0.812, 0.084]	[-1.254, 0.277]	[-0.803, 0.043]
	(-0.636, -0.368)	(-0.787, -0.044)	(-1.191, 0.170)	(-1.681, 0.416)	(-1.035, 0.113)
Share identified	1.00	0.96	0.27	0.37	0.33
N overall	725	725	725	725	725
N auctions	52	52	52	52	52
N without auctions	207	207	207	207	207

Notes: Impact of a one standard deviation SNB Bill signalling shock identified with sign and zero restrictions. Each column shows a different restriction. First, we only restrict the exchange rate or stock prices, without restricting the short-term interest rate. Then, we restrict the risk premium, inflation expectations, or the term spread. 90% and 95% confidence intervals are shown in brackets and parentheses, respectively. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the share of bootstrap replications for which $\tilde{\Omega}_{11} > 0$ or $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified), the overall number of observations to estimate the parameters (N overall), the number of observations to estimate $\Omega_{t\in A}$ (N auctions), and $\Omega_{t\notin A}$ (N without auctions). Note that N overall = N auctions + N without auctions + N other events. We remove N other events from the computation of the variance covariance matrices.

Seventh, we use the IV estimator proposed by Rigobon and Sack (2004) and provide an F-test for weak instruments proposed by Lewis (2020). This model is a special case of our approach estimating the responses to only one shock. We estimate two versions of the model, associating the shock either with stock prices or the exchange rate. Specifically, we estimate

$$y_t = \alpha + \beta \Delta s_t + \varepsilon_t$$

and

$$y_t = \alpha + \beta \Delta x_t + \varepsilon_t$$

for various outcomes y_t. As both, stock prices (s_t) and the exchange rate (x_t) are driven not only by SNB Bill shocks but also other factors, we use an IV estimator to estimate β with the instrument Z_t^i for $i \in \{s, x\}$ constructed as (see Rigobon and Sack 2004):

$$Z_t = [\mathbf{1}\{t \in A\} - \mathbf{1}\{t \notin A\}]\, e_t^i$$

where $\mathbf{1}\{t \in A\}$ and $\mathbf{1}\{t \notin A\}$ are indicator functions that equal one on auction and non-auction

Table D.9 — Robustness tests: IV estimates of SNB Bill shock working trough stock prices

	ON interest rate (in pp)	8Y interest rate (in pp)	Exchange rate (in %)
Fall in stock prices	0.003^{*}	-0.015^{***}	-0.168^{***}
by -1%	(0.002)	(0.002)	(0.028)
Constant	-0.001	-0.002	-0.039^{**}
	(0.001)	(0.001)	(0.018)
Foreign controls	yes	yes	yes
Robust first-stage F	518.1	518.1	518.1
Observations	725	725	725
R^2	0.002	0.264	0.108
Adjusted R^2	-0.005	0.259	0.102

Notes: IV estimates of the effect of an SNB Bill shock. Normalized to a minus one percent change in stock prices. Foreign controls omitted for brevity. A low heteroskedasticity-robust F-statistics of the first-stage regression indicates that the instrument is weak. Lewis (2020) recommends a rule-of-thumb of $F > 23$. Heteroskedasticity and autocorrelation consistent standard errors in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

days, respectively, and zero otherwise. In addition, e_t^i for $i \in \{s, x\}$ are residuals of a regression of stock price and the exchange rate changes on the exogenous variables, respectively.

Tables D.9 and D.10 show the results. For comparability with our baseline, we normalize the responses to correspond to a 1% decline in stock prices and the exchange rate, respectively. The F-statistic is well above 23, which is the recommended value by Lewis (2020). This suggests that the instruments are strong and we can use conventional methods for inference. The results are qualitatively similar to the estimates in Table D.8, where we only restrict either the exchange rate

Table D.10 — Robustness tests: IV estimates of SNB Bill shock working trough the exchange rate

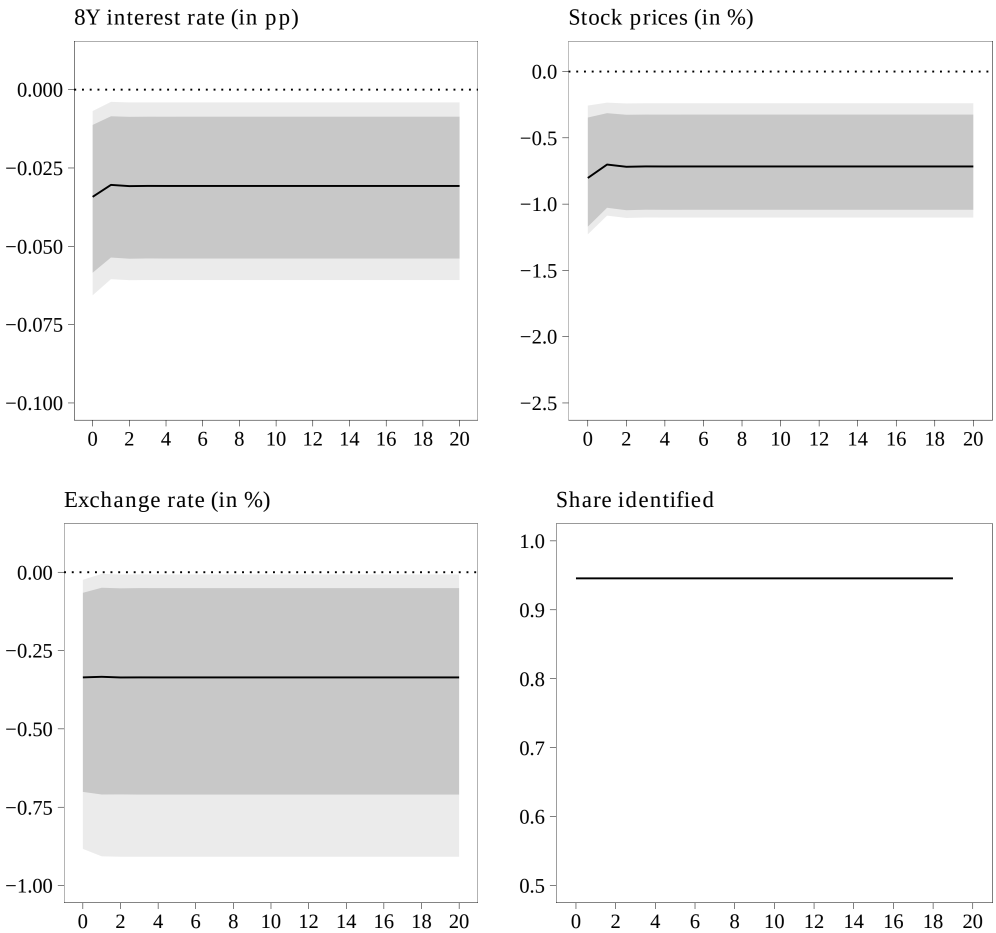
	ON interest rate (in pp)	8Y interest rate (in pp)	Stock prices (in %)
Fall in exchange rate	0.008**	−0.018***	−0.757***
by -1%	(0.003)	(0.005)	(0.110)
Constant	−0.001*	−0.001	0.016
	(0.001)	(0.001)	(0.035)
Foreign controls	yes	yes	yes
Robust first-stage F	1612.9	1612.9	1612.9
Observations	725	725	725
R^2	0.018	0.138	0.189
Adjusted R^2	0.011	0.132	0.183

Notes: IV estimates of the effect of an SNB Bill shock. Normalized to a minus one percent change in the exchange rate. Foreign controls omitted for brevity. A low heteroskedasticity-robust F-statistics of the first-stage regression indicates that the instrument is weak. Lewis (2020) recommends a rule-of-thumb of $F > 23$. Heteroskedasticity and autocorrelation consistent standard errors in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

or stock prices. The size of the effects are different, however, even when taking into account the different normalization. This may be due to the fact that we do not control for other events, which may reduce the difference in the variance between auction and non-auction days.

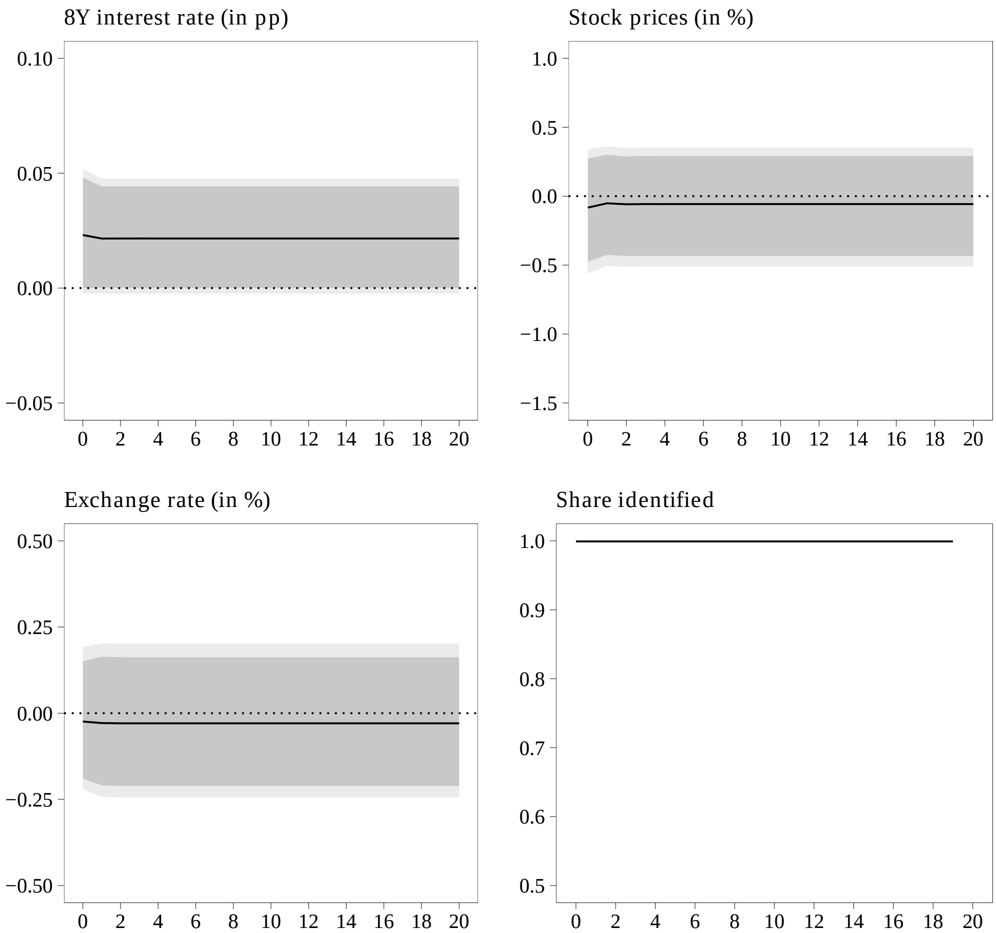
Finally, we use a VAR approach to estimate dynamic effects (see Appendix C). A VAR is more efficient as we have to estimate fewer coefficients than when using local projections. In addition, we have to impose the identifying assumption only on the initial response. The downside is that a VAR of a low lag order may be misspecified. The results are qualitatively identical, but, more precisely estimated.

Figure D.1 — Robustness tests: VAR impulse response to a signalling shock



Notes: Dynamic daily impact of a one standard deviation signalling shock identified with sign and zero restrictions. We assume that a signalling shock leads to a decline in stock prices but no change in the overnight interest rate. The impulse responses are based on a VAR model of order 1. Shaded areas give 90% and 95% confidence intervals. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the the share of bootstrap replications for which $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified).

Figure D.2 — Robustness tests: VAR impulse response to a overnight rate shock



Notes: Dynamic daily impact of a one standard deviation overnight rate shock identified with heteroscedasticity. We assume that an overnight rate shock leads to an increase in the overnight interest rate. The impulse responses are based on a VAR model of order 1. Shaded areas give 90% and 95% confidence intervals. Inference is based on 8,000 draws from a block bootstrap algorithm. We also report the the share of bootstrap replications for which $\tilde{\Omega}_{22} - \psi_{s1}^2 > 0$ (share identified).