

Informative trading or just costly noise? An analysis of Central Bank interventions[☆]

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Abstract

We conduct an empirical investigation of the impact of Central Bank intervention on the process of price formation in foreign exchange markets. The main contributions of this paper are (i) in considering the effects of official interventions on multiple dimensions of such a process beyond the first and second moment of currency returns and (ii) in exploiting insights from the analysis of market liquidity in proximity of these trades to explain their effectiveness. For that purpose, we employ a unique dataset of tick-by-tick indicative quotes and intraday (informative) sterilized spot interventions and (uninformative) customer transactions executed by the Swiss National Bank (SNB) on the Swiss Franc/U.S. Dollar exchange rate (CHFUSD) between 1996 and 1998. Using several empirical strategies (some of which are novel to the exchange rate literature), we find that the effectiveness of these trades is crucially related to their perceived information content, rather than to imperfect substitutability or inventory considerations. Indeed, regardless of their size, only SNB interventions (especially when unexpected or leaning against the wind) have significant and persistent effects on daily CHFUSD returns, although they often fail to smooth currency fluctuations. Nonetheless, only SNB interventions, regardless of their effectiveness, induce significant misinformation and heterogeneity of beliefs among market participants and deteriorate market liquidity. These

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externalities always translate into higher, economically significant transaction costs borne by investors.

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1. Introduction

Central Bank interventions are one of the most interesting and puzzling features of the global foreign exchange (forex) markets. Central Banks often engage in individual or coordinated efforts to influence exchange rate dynamics, either to strengthen or resist market momentum, to calm disorderly market conditions, to signal current or future economic policies, or to replenish previously depleted reserves. There is strong consensus in the economic literature (e.g., [Adams and Henderson, 1983](#)) that *unsterilized* interventions, by affecting the existing stock of high-powered money, influence the exchange rate through the traditional channels of monetary policy. The effectiveness and necessity of *sterilized* interventions, i.e., those accompanied by offsetting actions on the domestic monetary base, are instead still controversial, and, as such, at the center of the current theoretical and empirical debate.¹

Within the standard macroeconomic approach, sterilized interventions may affect the exchange rate through either of two channels: imperfect substitutability or signaling. The first channel is usually examined in the context of portfolio balance models (e.g., [Branson, 1983, 1984](#)) in which risk-averse market participants need to be compensated for holding sub-optimal portfolios following the intervention. The second channel ([Mussa, 1981; Bhattacharya and Weller, 1997](#)) allows sterilized intervention to affect prices by conveying not only information on policy intentions, but also fundamental information about the future value of the currency. Yet, according to [Dominguez \(2006, p. 1052\)](#), “neither of these channels is easily reconciled with the empirical evidence” on whether and how interventions influence exchange rate movements and volatility, especially in the short run.²

Within the newer market microstructure approach to currency determination (see [Lyons, 2001; Evans and Lyons, 2002](#)), theoretical research concentrates on the process through which traders revise their expectations and dealers adjust prices, either temporarily or permanently, in response to sterilized interventions (e.g., [Evans and Lyons, 2003; Vitale, 2003; Pasquariello, 2005](#)). Two recent empirical advances, surveyed in depth by [Neely \(2005\)](#), have enhanced our understanding of these mechanisms. The first is

¹See [Sarno and Taylor \(2001\)](#) for a survey.

²The empirical literature on imperfect substitutability (see [Edison, 1993](#) for a review), with the exception of [Dominguez and Frankel \(1993a\)](#), finds that portfolio balance effects of official interventions on exchange rates are small and short-lived in the 1970s and the 1980s. More recently, however, [Evans and Lyons \(2003\)](#) show that even sterilized, secret, and uninformative Central Bank trades may impact exchange rates if they generate interdealer order flow. There is somewhat stronger evidence in support of the signaling channel (e.g., [Dominguez, 1987; Kaminsky and Lewis, 1996; Payne and Vitale, 2003](#)).

the availability of high frequency data on both exchange rates and Central Bank interventions. The second is the use of event studies to examine the behavior of exchange rates in proximity of intervention dates or trades with minimal assumptions about the data-generating process. Along these lines, many studies concentrate on the impact of these transactions on daily or intraday exchange rate returns and return volatility.³

Despite its promise and encouraging results, this research also suffers from several limitations. High-frequency exchange rate data are in fact plagued by microstructure frictions, many of which are potentially relevant over intraday event intervals. Further, both interventions and exchange rate fluctuations are likely to be determined simultaneously, since Central Banks respond to undesired market conditions. Endogeneity biases may then affect both significance and interpretation of estimates of the contemporaneous reaction of the exchange rate to Central Bank transactions. The analysis of intraday event windows around precise event times can only attenuate, but does not eliminate this concern, since interventions may display their full effects over days or weeks.⁴ Finally, most event studies examine the impact of interventions on specific facets of the forex market in isolation, hence ignoring both their interaction and the additional information they may provide to evaluate the effectiveness of these policies. Instead, the presence of active price manipulators in the otherwise very liquid and (widely recognized as) efficient forex markets raises a broader question: what is the impact of interventions on the process of price formation in the currency market as a whole, hence not only on exchange rate dynamics but also on the market's ability to process information and investors' ability to trade? This question, albeit of interest to investors, analysts, and policymakers, has so far received little attention.⁵

Addressing this question is the main contribution of our study. We do so by bridging both the macro and microstructure literature on Central Bank intervention. Specifically, we investigate sterilized spot interventions and *passive trades* (commonly labeled “customer transactions”) executed by the Swiss National Bank (SNB)—the Swiss Central Bank—on the Swiss Franc/U.S. Dollar exchange rate (CHFUSD) between 1986 and 1998. The CHFUSD is among the most liquid currency pairs traded in the global forex markets, the SNB is one of the most credible monetary authorities in the financial world, and its interventions are contemporaneously publicly available. Although SNB interventions may be informative about economic fundamentals and policy motives, customer transactions are not, since they are conducted by the SNB for reasons other than exchange rate management. We then build a database matching those transactions with tick-by-tick quotes posted by dealers on Reuters terminals and use them to compute *daily* exchange rate returns and measures of ex post volatility, transaction costs, and trading intensity. By studying the lower-frequency impact of intraday SNB trades on daily aggregates, we focus

³Recent examples include Fischer and Zurlinden (1999), Humpage (1999), Dominguez (2003, 2006), Fatum and Hutchison (2003), Pasquariello (2003), and Payne and Vitale (2003). Neely (2005) provides an exhaustive survey and discussion of strengths and weaknesses of this branch of the intervention literature.

⁴From a policy perspective, short-term horizons may not be sufficient to establish the effectiveness of interventions in moving exchange rates. For instance, 40% of the central bankers surveyed in Neely (2000) believe that their actions require at least a few days to be fully reflected in the target currency.

⁵For instance, most of the recent empirical studies of the microstructure of the forex markets in proximity of Central Bank interventions surveyed in the Appendix of Neely (2005) concentrate on either exchange rate returns, return volatility, or both. Recent studies of the impact of official interventions on bid-ask spreads include Bossaerts and Hillion (1991), Naranjo and Nimalendran (2000), D'Souza (2002), and Chari (2006).

on longer horizons—of relevance to policymakers—without discarding valuable intraday information, while minimizing potential distortions to the inference from microstructure frictions.⁶ Further, inference from the estimated impact of SNB trades on market liquidity is less likely to be biased by endogeneity considerations, since transaction costs and trading intensity are less likely to enter the reaction function of a Central Bank in a significant way. However, insights from the analysis of market liquidity in proximity of its interventions can be exploited to learn about the nature of their effectiveness.

Our analysis proceeds in two stages. In the first stage, to motivate our effort, we use an event study methodology to examine the cumulative impact of SNB trades on each of those daily aggregates separately over an interval of roughly three weeks around the event dates. We find that SNB interventions, despite accounting for only a small portion of the average daily turnover in the CHFUSD market, significantly affect these variables both in the short and long run. Regardless of their size, SNB interventions are unforeseen (except those chasing the trend) and have persistent effects on currency returns (lasting for several days after their execution), especially when against existing momentum. The SNB is much less successful in calming disorderly market conditions: *ex post* measures of currency volatility always surge in proximity of its trades and stay high for many days afterward. These trades are nonetheless costly: absolute and proportional spreads often widen in their proximity, and market liquidity deteriorates. The surge in spreads is economically significant as well: we estimate that (annualized) transaction costs borne by investors and speculators increase by almost \$150 million when the SNB sells USD and by over \$815 million when the SNB buys USD. These results are robust to several extensions and variants of our basic empirical strategy, as well as to the inclusion of potentially important economic variables for the decision-making process of both the SNB and the Federal Reserve.

In the second stage, we assess the relative importance of inventory, risk-aversion, adverse selection, and information considerations in explaining those non-trivial changes in exchange rate returns, return volatility, and market liquidity. For that purpose, we extend the existing literature in three directions. First, we repeat our preliminary analysis for a control sample made of all customer transactions executed by the SNB over the sample period. Indeed, since these transactions are by their nature uninformative, they provide a unique benchmark to gauge the relevance of the information content of SNB trades on the effects described above. We find that those transactions have a negligible impact on the many dimensions of the microstructure of the CHFUSD market.⁷

Second, we estimate a series of bivariate vector autoregression (VAR) models of auto- and cross-correlations between interventions and either quote revisions, spreads, or trading intensity (i) to account for their potentially simultaneous determination and (ii) to identify the unexpected component of each SNB trade, without making explicit assumptions on the structure of their interaction. Within this setting, any permanent impact of these trades on quotes or market liquidity can be attributed solely to its surprise information content, rather than to transient inventory effects (Hasbrouck, 1988, 1991). The ensuing evidence indicates that, when unanticipated, SNB interventions have an even more pronounced

⁶E.g., see the discussion in Andersen, Bollerslev, Diebold, and Labys (2003).

⁷Using a similar database, Fischer and Zurlinden (1999) and Payne and Vitale (2003) analyze execution prices and four-hour windows around intraday SNB trades, respectively, and find evidence of a significant (but only partially persistent) short-term impact of only its interventions on intraday CHFUSD returns.

directional effect on the Swiss Franc, again at the cost of even greater volatility and transaction costs borne by investors.

Third, we focus explicitly on shocks to transaction costs in proximity of SNB interventions. Specifically, we decompose daily bid–ask spread shocks during those trades into shocks related to misinformation, liquidity, fundamental volatility, competition, and immediacy using a reduced-form model (adapted from Fedenia and Grammatikos, 1992) for the many theories of spread determination in the market microstructure literature. We then use the relative significance of these arguments to interpret the impact of SNB interventions on CHFUSD returns and return volatility. Estimation of the model reveals that information and liquidity shocks, but not portfolio balance effects, explain the increase in transaction costs typically accompanying SNB transactions. In particular, especially when large and chasing an existing trend, these trades induce the greatest heterogeneity of beliefs among market participants, which translates into a small impact on currency returns and wider spreads.⁸

Overall, our empirical analysis suggests that Central Bank interventions have important effects on the many dimensions of the process of price formation in the currency markets, and that information (rather than inventory or portfolio balance) considerations are the single most important determinant of these effects. Nonetheless, regardless of their effectiveness in influencing the dynamics of the target exchange rate, official interventions appear to cause severe externalities—often in the form of deteriorating market liquidity—that cannot be exclusively attributed to adverse selection. Hence, Central Banks may face an economically significant trade-off between (mis)information and transaction costs when formulating and executing their currency management policies.

The paper is organized as follows. Section 2 describes our dataset. In Section 3 we analyze the reaction of currency returns, return volatility, and market liquidity to SNB transactions in isolation, explore the relevance of important attributes of these trades (size, momentum, expectations) for our findings, and perform several robustness checks. The decomposition of estimated spread shocks during SNB interventions is in Section 4. Section 5 concludes.

2. Data

2.1. Central Bank transactions

Most datasets of official interventions include exclusively daily or weekly amounts of domestic currency negotiated in secret by the Central Bank. Further information on these transactions (e.g., time of execution or settlement price) is generally unavailable. Some authors construct richer time series of interventions using the history of newswire reports

⁸In a related study, Naranjo and Nimalendran (2000) use both structural and time-series models for daily Bundesbank and Federal Reserve interventions in the Deutschemark/U.S. Dollar market between 1976 and 1994 to identify their unanticipated components, find a positive relation between the variance of the latter and daily (New York open or midday) bid–ask spreads after controlling for inventory and order processing costs, and attribute that relation to adverse selection. Peiers (1997) studies time-stamped news on Bundesbank interventions in the same market between 1992 and 1993 and shows that these transactions generate information-based leadership among forex dealers.

(e.g., Chang and Taylor, 1998; Dominguez, 2003; Chari, 2006). However, media reports on interventions are often inaccurate and almost never mention their volumes.⁹ In this research, in order to study the impact of interventions on the daily process of price formation in the currency markets, we use a unique database made of all intraday spot, ex post announced transactions conducted by the SNB on CHFUSD between 1986 and 1998.¹⁰

As early as 1975 (following the collapse of the Bretton Woods Agreement) and over the course of our sample period, the SNB developed and implemented a monetary policy based largely on monetarist principles (i.e., targeting the growth of monetary aggregates), in pursuit of the ultimate goal of price stability (Rich, 1997; Peytrignet, 1999). Yet, the SNB often interpreted its monetary targets pragmatically and intervened on the Swiss Franc “to offset the negative effects of exchange market disorder” (Peytrignet, 1999, p. 214) or unexpected exchange rate shocks on the Swiss economy. During the late 1970s, the SNB occasionally abandoned its fight against inflation to deal with the recurring strength of the domestic currency. The inflationary wave of the early 1980s led the SNB to adopt intermediate, restrictive annual targets for the monetary base and to a three-year hiatus in its intervention activity. The SNB resumed its interventions in November 1986, in response to recession fears,¹¹ and ended it in August 1995, following the introduction of multi-year monetary targets. According to Fischer and Zurlinden (1999, p. 664), throughout this interval the SNB intervened principally “to affect the trend of the exchange rate or to counteract market disturbances,” although “solidarity with other Central Banks may also have been an important motive.”

Trades executed on behalf of the SNB in the spot forex markets are of two types: *interventions* and *customer transactions*. Nearly all SNB interventions in the dataset are sterilized (i.e., accompanied by offsetting actions on the domestic monetary base), ex ante unannounced, and coordinated: the Bundesbank and/or the Federal Reserve intervene on the same day and in the same direction as the SNB.¹² Customer transactions are purchases and sales of USD triggered by the Swiss government’s requests for foreign and domestic currency. For example, when the government needs dollars, the SNB supplies them by reducing its USD holdings. This leads to a steady outflow of dollars from the SNB’s reserves. Thus, the SNB defines customer transactions as all transactions conducted to replenish (usually not immediately) its reserves depleted by actions of the true customer

⁹For more on the accuracy of newswire reports for Central Bank interventions, see Osterberg and Wetmore Humes (1993, 1995) and Fischer (2003).

¹⁰A detailed description and preliminary intraday analysis of this dataset can be found in Fischer and Zurlinden (1999) and Payne and Vitale (2003).

¹¹Consistently, Peytrignet (1999, p. 198) observes that “whenever there is a rise in the external value of the Swiss currency sufficient to seriously threaten economic conditions in [Switzerland], the fight against such an increase has taken priority over meeting a monetary target.”

¹²However, according to Fischer (2004, p. 6), this does not imply that “the SNB has always followed the lead of the Federal Reserve and the Bundesbank.” For example, between 1986 and 1995, “these two Central Banks have intervened more frequently than the SNB has.” Furthermore, the available literature (e.g., see the surveys of Edison, 1993 and Sarno and Taylor, 2001) indicates that both the Bundesbank and the Federal Reserve routinely sterilized most of their forex intervention operations with open market trades over the sample period. There are only three days when the SNB acted alone in the CHFUSD market (December 27, 1989 and March 6 and 11, 1992), and only in these cases it did not neutralize in full the effect of its actions on domestic liquidity. We remove those days from the sample.

(the government) or, more generally, motivated by reasons other than exchange rate management. Hence, these transactions are ex post uninformative.

Immediately after a trade is completed, the SNB informs the counterparty of the nature of the transaction, i.e., whether it represents an intervention. Fischer and Zurlinden (1999) observe that intervention announcements spread rapidly across the market and are quickly picked up by news agencies. It is then reasonable to assume that dealers experience no difficulties in identifying the SNB as a counterparty and, together with all other market participants, in distinguishing interventions from customer transactions after their execution. For each transaction, the SNB reports the amounts traded, the negotiated price, and the (Zurich) time of occurrence, rounded to the nearest minute. All data refer to single transactions executed at the given time by the SNB. The SNB does most of its forex transactions with Zurich-based banks, including local branches of foreign intermediaries. Each counterparty does not know the total daily amount of the SNB action (if made up of several trades with different dealers).

The upper panel of Table 1 collects descriptive statistics on intraday SNB interventions, I_{it} , and customer transactions, C_{it} , where i is the i th trade on day t . In the lower panel of Table 1 we aggregate these trades on a daily basis. The resulting cumulative daily SNB interventions (I_t) and customer transactions (C_t) are then plotted in Fig. 1 over the sample period. Between 1986 and 1998, the SNB intervenes 709 times in 102 days, and executes 555 customer transactions in 326 days. Although SNB trades are in both directions, about two-thirds of the interventions are dollar sales (i.e., negative), while most customer transactions are (as expected) dollar purchases (i.e., positive). In particular, there are 86 days in the sample when only official interventions (I) are observed. In 18 of these the SNB purchases USD ($I > 0$), while it sells USD ($I < 0$) in the remaining 68. Customer transactions (C) are more frequent. There are 310 days in which they occur: dollar purchases ($C > 0$) take place in 298 of them, dollar sales ($C < 0$) just in 12. There are also 16 days in which the SNB buys dollars both as interventions and customer transactions ($I \& C$). Official dollar sales ($I_t < 0$) occur mostly between 1989 and 1992, following the sharp decline in the Swiss Franc accompanying the Bundesbank's tight monetary policy (Rich, 1997). Official dollar purchases ($I_t < 0$) are scattered throughout the rest of the sample period.

Signed individual intraday interventions and customer transactions have the same median size (\$10 million), yet daily aggregate interventions (I_t) are larger on average than customer transactions (C_t) of the same sign, even when on the same day ($I_t^{\&}$ and $C_t^{\&}$). Indeed, the SNB tends to execute numerous intervention trades within a single day (81% of them within one hour of each other), rarely for amounts larger than \$20 million, and with different counterparties (7 on average). According to Fischer (2003), this strategy is aimed at disseminating intervention news as broadly as possible in the dealer market. Customer transactions are less concentrated on particular days, and are often executed with just one dealer.¹³ Nonetheless, both transactions represent only a very small fraction of the mean daily turnover in the CHFUSD market (around \$80 billion) estimated by the Bank for International Settlements (BIS, 1999).¹⁴

¹³In the upper panel of Table 1, the mean number of customer transactions per day is 1.69.

¹⁴The BIS (1999) triennial survey of currency market activity for 1998 reports that about \$1.5 trillion in transactions are executed in the global forex market every day, of which approximately 5% is explained by trading in CHFUSD (thereby making it the fourth most traded currency pair).

Table 1

Descriptive statistics on intraday SNB transactions on CHFUSD

The upper panel reports descriptive statistics for intraday (t_i) SNB trades over days between April 17, 1986 and December 23, 1998 when either an intervention (I_{t_i}), a customer transactions (C_{t_i}), or both ($I_{t_i}^{\&}$ and $C_{t_i}^{\&}$) occurred. Amounts are in millions of U.S. Dollars. A positive (negative) value for I_{t_i} or C_{t_i} represents a purchase (sale) of dollars. N is the number of observations. d is the number of dealers trading with the SNB for a given day. *Skew* is the coefficient of skewness, while *Kurt* is the excess kurtosis; their standard errors for asymptotic normal distributions are $(\frac{6}{N})^{\frac{1}{2}}$ and $(\frac{24}{N})^{\frac{1}{2}}$, respectively. A “*” indicates statistical significance at the 10% level. In the case of d , a “*” indicates that its mean (μ_d) is statistically different from 1 at the 10% significance level. The lower panel reports corresponding descriptive statistics for aggregate daily (t) SNB trades.

	Type of intraday SNB transaction							
	I_{t_i}	$I_{t_i} > 0$	$I_{t_i} < 0$	C_{t_i}	$C_{t_i} > 0$	$C_{t_i} < 0$	$I_{t_i}^{\&}$	$C_{t_i}^{\&}$
N	602	136	466	523	501	22	107	32
Mean	−5.38	8.35	−9.39	16.63	17.75	−8.95	8.46	10.20
Median	−5	10	−10	10	10	−10	10	10
St. dev	9.85	3.34	7.14	23.65	23.52	3.58	3.10	4.93
Min	−100	5	−100	−18	0.70	−18	5	4.50
Max	35	35	−5	200	200	−1	25	20
Skew	−1.67*	3.53*	−6.37*	3.87*	4.02*	0.20	1.52*	0.60
Kurt	16.13*	28.91*	63.74*	19.71*	20.38*	1.89*	7.51*	−0.61
μ_d	7.00*	7.56*	6.85*	1.69*	1.68*	1.83*	6.69*	2.00*
σ_d	5.35	4.63	5.55	1.36	1.38	0.72*	5.29*	1.83*
Min d	1	1	1	1	1	1	1	1
Max d	36	20	36	10	10	3	21	8

	Type of daily SNB transaction							
	I_t	$I_t > 0$	$I_t < 0$	C_t	$C_t > 0$	$C_t < 0$	$I_t^{\&}$	$C_t^{\&}$
N	86	18	68	310	298	12	16	16
Mean	−37.67	63.06	−64.34	28.05	29.84	−16.42	56.56	20.40
Median	−30	50	−50	15	15	−20	45	15
St. dev	93.74	32.86	86.17	57.76	58.18	8.16	37.67	19.19
Min	−545	25	−545	−30	1	−30	10	4.50
Max	150	150	−20	800	800	−1	130	70
Skew	−2.98*	1.25*	−4.49*	8.79*	8.87*	0.56	0.91	1.75*
Kurt	14.98*	1.38	22.07*	106.7*	106.8*	−0.05	−0.38	2.23*

2.2. CHFUSD quotes

The exchange rate dataset used in this study consists of all the quotes for CHFUSD posted on the interbank Reuters FAFX screen (and there continuously recorded by Olsen & Associates) between February 3, 1986 and December 31, 1998. Each quote contains a bid price (B_{t_n}), an ask price (A_{t_n}), and the Greenwich mean time (GMT) when it first appears on the Reuters terminals, rounded to the nearest second. These quotes are irregularly spaced in time, simply indicative (i.e., non-binding), and plagued by transmission delays and many microstructure frictions (e.g., clustering of the posted bid–ask spreads and strategic quote positioning) extensively studied in the

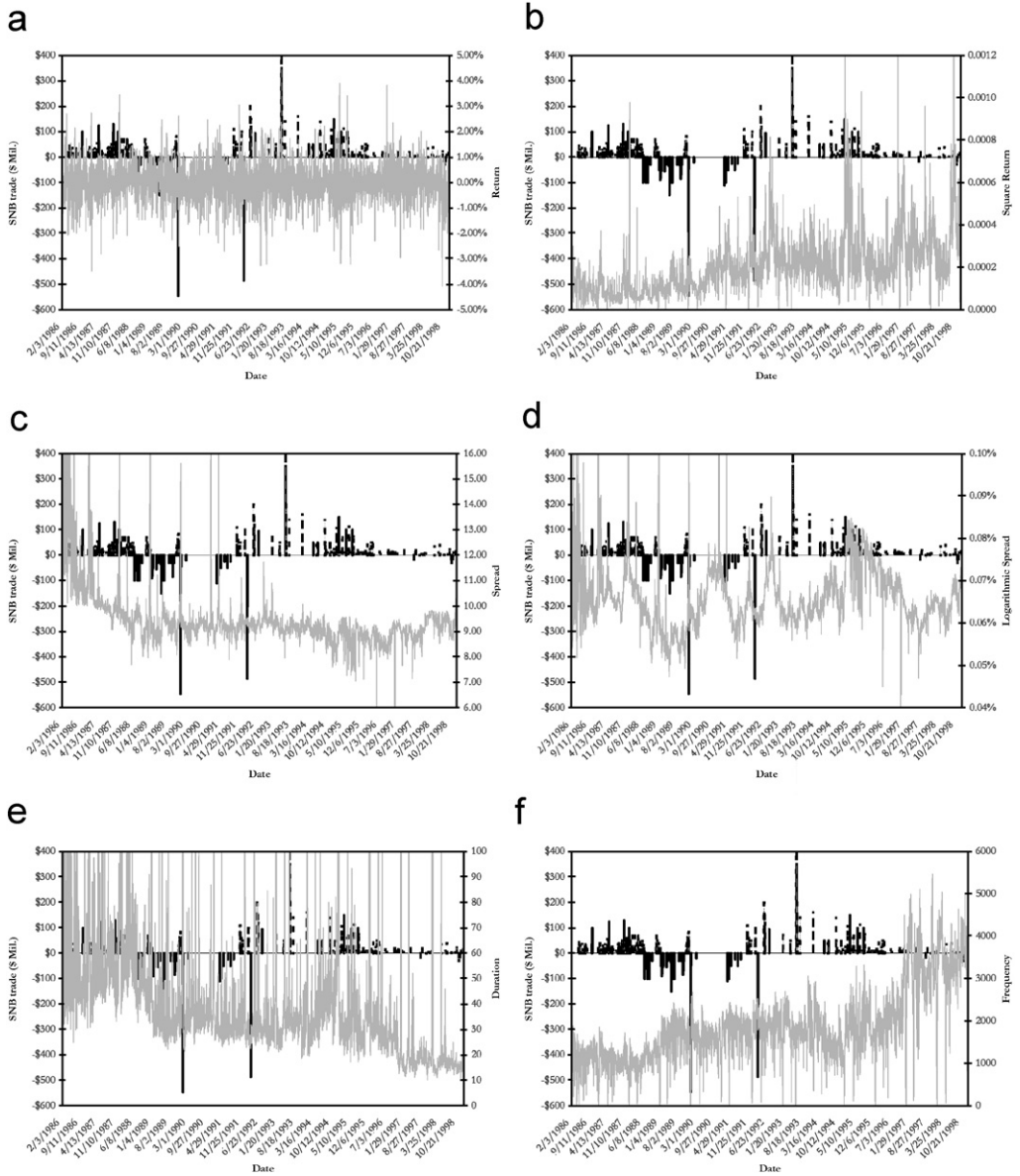


Fig. 1. SNB trades and CHFUSD grouped variables: daily plots. These figures plot r_t , r_t^2 , S_t , s_t , d_t , and f_t (gray lines, right axis), as well as the cumulative daily SNB interventions (left axis, solid histogram) and customer transactions (left axis, dotted histogram) over the sample period between January 2, 1986 and December 31, 1998. r_t is the cumulative daily return over day t . The square return, r_t^2 , is a proxy for daily exchange rate volatility. S_t is the average bid–ask spread (in pips, i.e., currency units times 10^4) over day t , while s_t is the average logarithmic bid–ask spread over day t . Finally, the duration variable d_t is the average length of time (in seconds) between consecutive quotes posted on the Reuters terminals over day t , while the frequency variable f_t is the number of posted quotes over day t . (a) Return r_t ; (b) square return r_t^2 ; (c) absolute spread S_t ; (d) logarithmic spread s_t ; (e) duration d_t ; and (f) frequency f_t .

literature.¹⁵ As suggested by Andersen, Bollerslev, Diebold, and Labys (2003), these frictions, although typically relevant over intraday intervals, become immaterial for statistical analyses of longer-horizon aggregates. Thus, we focus our investigation on daily measures of exchange rate behavior, ex post volatility, market liquidity, and trading intensity constructed using those intraday quotes.¹⁶

As in Müller, Dacorogna, Olsen, Pictet, Schwarz, and Morgenegg (1990) and Andersen and Bollerslev (1997), we define the n th tick-by-tick midquote return for day t , r_{t_n} , as¹⁷

$$r_{t_n} = \frac{1}{2}[\ln(B_{t_n}) + \ln(A_{t_n})] - \frac{1}{2}[\ln(B_{t_{n-1}}) + \ln(A_{t_{n-1}})]. \quad (1)$$

We measure the tick-by-tick absolute bid–ask spread as $S_{t_n} = (A_{t_n} - B_{t_n}) \times 10,000$ (i.e., in pips). Consistent with Eq. (1), we use the logarithmic spread $s_{t_n} = \ln(A_{t_n}) - \ln(B_{t_n})$ as a proxy for the proportional spread. We also compute tick-by-tick absolute returns $|r_{t_n}|$, tick-by-tick duration d_{t_n} as the length of time (in seconds) between consecutive quotes, and frequency f_t as the number of posted quotes over day t . We then define the cumulative return over day t , r_t , as $r_t = \sum_{n=1}^{f_t} r_{t_n}$. Further, we compute two estimates of daily CHFUSD return volatility from intraday return data. The first one is the cumulative absolute return over day t , $|r_t|$, given by $|r_t| = \sum_{n=1}^{f_t} |r_{t_n}|$. Daily absolute returns $|r_t|$ may capture not only market volatility (e.g., Payne and Vitale, 2003) but also the intensity of informational events and information shocks (e.g., Chordia, Shivakumar, and Subrahmanyam, 2004). Alternatively, we also compute the square return measure r_t^2 of Andersen, Bollerslev, Diebold, and Labys (2001, 2003), by summing the squared intraday CHFUSD returns r_{t_n} over each day t , i.e., $r_t^2 = \sum_{n=1}^{f_t} r_{t_n}^2$.¹⁸ Andersen, Bollerslev, Diebold, and Labys (2001, 2003) argue that the resulting daily realized exchange rate volatility series is a better proxy for current exchange rate volatility than those from standard models based on daily data (such as GARCH or RiskMetrics), since the former captures valuable intraday information while the latter, slowly decaying moving averages, react only gradually to volatility shocks.¹⁹ This feature makes the realized squared return a more suitable tool to

¹⁵See Goodhart and O'Hara (1997) and Dacorogna, Gençay, Müller, Olsen, and Pictet (1996) for a review. Bessembinder (1994) and Hasbrouck (1999) analyze the clustering in indicative quotes on DEMUSD. Bollerslev and Melvin (1994) suggest that reputation effects may prevent the posting of quotes at which a bank would not subsequently be willing to trade. Goodhart, Ito, and Payne (1996) compare those quotes with a short sample of spot transactions and find that intraday indicative spreads generally overestimate actual spreads (and the relevance of clustering) but may underestimate them during highly volatile periods.

¹⁶Using standard filtering procedures recommended by Bollerslev and Domowitz (1993), Dacorogna, Müller, Nagler, Olsen, and Pictet (1992), and Andersen and Bollerslev (1997), we eliminate about 11% of the original observations, but still remain with slightly less than 6.3 million validated intraday quotes over 3,352 trading days.

¹⁷These returns, only negligibly different from conventional midquote log-returns, have the advantage of being symmetric with respect to the denomination of the exchange rate.

¹⁸In particular, Andersen, Bollerslev, Diebold, and Labys (2001, 2003) show that, under suitable conditions, r_t^2 , the realized sample path variation of the square return process $r_{t_n}^2$ over day t , is an unbiased (and asymptotically free of measurement error) estimator of daily return volatility conditional on information on day $t - 1$. In a concurrent study, Dominguez (2006) employs this measure to analyze the impact of G-3 interventions on daily Deutschmark/Dollar and Yen/Dollar volatility.

¹⁹In Andersen, Bollerslev, Diebold, and Labys' (2003, p. 613) words, "[s]uppose, for example, that the true volatility has been low for many days, $t = 1, \dots, T - 1$, so that both realized and GARCH volatilities are presently low as well. Now suppose that the true volatility increases sharply on day T [e.g., in response to an official intervention] and that the effect is highly persistent as is typical. Realized volatility for day T , which makes effective use of the day- T information, will increase sharply as well, as is appropriate. GARCH or RiskMetrics volatility, in contrast, will not change at all on day T , as they depend only on squared returns from days

Table 2

Descriptive statistics on CHFUSD grouped variables

The upper panel of this table reports summary statistics (defined in the notes to Table 1) for r_t , $|r_t|$, r_t^2 , S_t , s_t , d_t , and f_t computed over the interval January 2, 1986–December 31, 1998. r_t is the cumulative daily return over day t . The cumulative daily absolute return, $|r_t|$, and square return, r_t^2 , are proxies for daily exchange rate volatility. S_t is the average bid–ask spread (in pips, i.e., currency units times 10^4) over day t , while s_t is the average logarithmic bid–ask spread over day t . Finally, the duration variable d_t is the average length of time (in seconds) between consecutive quotes posted on the Reuters terminals over day t , while the frequency variable f_t is the number of posted quotes over day t . $\hat{\rho}_1$ is the estimated first-order autocorrelation. LB(5) is the value of the Ljung–Box test of randomness for up to the fifth-order serial correlation. The lower panel reports mean (μ) and standard deviation (σ) for each of these variables over the subsets of days when an event of type $h = I, I \geq 0, C, C \geq 0$ (defined in the notes to Table 1), or $I \& C$ occurred. $I \& C$ are days when the SNB executed both interventions and customer transactions. A “*” indicates significance at the 10% level.

	N	Mean	St. dev.	Skew	Kurt	$\hat{\rho}_1$	LB(5)
r_t	3,352	−0.0079%	0.7338%	−0.11*	2.23*	0.024	14.83*
$ r_t $	3,352	0.4216*	0.2175	1.01*	1.73*	0.527*	1099.4*
r_t^2	3,352	0.00020*	0.00014	1.99*	7.56*	0.472*	945.4*
S_t	3,352	9.4391*	1.2466	5.17*	44.31*	0.473*	946.6*
s_t	3,352	0.0659%*	0.0077%	2.35*	14.40*	0.503*	1023.0*
d_t	3,352	56.66*	275.4	20.78*	485.3*	0.084*	27.98*
f_t	3,352	1873.1*	868.9	0.90*	0.88*	0.541*	1156.3*
	I	$I > 0$	$I < 0$	C	$C > 0$	$C < 0$	$I \& C$
N	86	18	68	310	298	12	16
μ_{r_t} (σ_{r_t})	0.0252% (0.8861%)	0.0996% (1.0615%)	0.0055% (0.8416%)	−0.0865%* (0.6909%)	−0.0770%* (0.6807%)	−0.3200% (0.9150%)	0.0331% (1.2119%)
$\mu_{ r_t }$ ($\sigma_{ r_t }$)	0.3725* (0.1420)	0.3921* (0.2250)	0.3673* (0.1123)	0.3561* (0.2235)	0.3404* (0.2119)	0.7450* (0.1373)	0.2835* (0.1482)
$\mu_{r_t^2}$ ($\sigma_{r_t^2}$)	0.00018* (0.00012)	0.00023* (0.00020)	0.00017* (0.00009)	0.00018* (0.00016)	0.00017* (0.00016)	0.00034* (0.00008)	0.00019* (0.00014)
μ_{S_t} (σ_{S_t})	9.5964* (0.8371)	9.9968* (0.9202)	9.4905* (0.7872)	9.7111* (1.5797)	9.7470* (1.6003)	8.8202* (0.2268)	10.8434* (2.4286)
μ_{s_t} (σ_{s_t})	0.0625%* (0.0089%)	0.0724%* (0.0085%)	0.0598%* (0.0069%)	0.0678%* (0.0085%)	0.0680%* (0.0085%)	0.0625%* (0.0026%)	0.0794%* (0.0021%)
μ_{d_t} (σ_{d_t})	37.04* (11.12)	42.10* (12.16)	35.71* (10.52)	50.88* (63.87)	52.29* (64.75)	15.80* (1.68)	59.88* (29.58)
μ_{f_t} (σ_{f_t})	1648.2* (387.9)	1452.9* (396.8)	1699.9* (371.5)	1611.6* (874.7)	1529.5* (783.6)	3652.0* (435.4)	1158.4* (501.9)

capture the impact of SNB interventions on the unobservable true volatility. Finally, we define S_t , s_t , and d_t as the arithmetic means of S_{t_n} , s_{t_n} , and d_{t_n} over day t .

Table 2 reports summary statistics for each of these variables, while Figs. 1a–f plot their realizations, over the entire sample period as well as over each subset of days during which the SNB traded (as defined in Section 2.1). The basic statistical properties of these data are well known in the literature (e.g., Andersen and Bollerslev, 1997; Payne and Vitale, 2003; Dominguez, 2006). Therefore, we discuss them only briefly. The distribution of cumulative daily CHFUSD returns r_t is almost symmetrically centered around zero and displays fat

(footnote continued)

$T - 1, T - 2, \dots$, and they will increase only gradually on subsequent days, as they approximate volatility via a long and slowly decaying exponentially weighted moving average.”

tails; r_t 's estimated first-order autocorrelation ($\hat{\rho}_1$) is statistically insignificant, but a standard test for randomness rejects the null hypothesis that returns are white noise. As expected, both proxies for within-day return volatility ($|r_t|$ and r_t^2) are strongly persistent. Further, realized CHFUSD return volatility is increasing over the sample interval (r_t^2 in Fig. 1b),²⁰ possibly reflecting the greater turbulence in the currency markets in the 1990s, as well as the crescent interest of forex traders and speculators in the Swiss Franc as a “safe haven” (Peytrignet, 1999).

Accordingly, a large (almost 1,900 on average) and increasing number of new CHFUSD quotes is posted every day on the Reuters terminals between 1986 and 1998 (f_t in Fig. 1f). The average duration between consecutive new quotes (d_t) is roughly one minute, but declines to less than 20 seconds by the end of 1998. The CHFUSD market is also highly and increasingly liquid: the mean absolute spread is around 9.43 pips, while the proportional bid–ask spread averages about 0.066%, smaller than in most equity markets. Nonetheless, both variables display pronounced fluctuations, and often appear to rise suddenly and sharply in proximity of SNB interventions. These observations underscore the need to control for trends in the analysis that follows. For instance, the Swiss Franc appears to be weaker, its market less liquid, and transaction costs higher, when the SNB purchases USD (column $I > 0$ in Table 2), yet so is the CHFUSD market when the majority of such interventions occur, in the earlier part of the sample. Finally, the evidence of positive autocorrelation for most of the variables suggests the presence of daily periodicity in the data. Indeed, when we compute (but do not report here) means of daily values for r_t , $|r_t|$, r_t^2 , S_t , s_t , and f_t over different days of the week, all variables, with the exception of r_t , show statistically and economically meaningful weekday patterns.²¹

3. Estimating the impact of SNB transactions

We are now ready to investigate the impact of SNB trades on the process of price formation in the CHFUSD market. Our analysis proceeds in two stages. In this section, we separately examine the behavior of each of the daily aggregate variables $X_t = r_t, |r_t|, r_t^2, S_t, s_t, f_t$, and d_t (defined in Section 2.2) in proximity of SNB interventions and customer transactions using various event study methodologies. This approach allows us to identify in an intuitive fashion the effects of these actions not only on exchange rate returns and return volatility, as is common in the literature, but also on many facets of market liquidity. Its simplicity, however, comes at the cost of some potentially serious limitations, since Central Bank interventions and exchange rates are likely to be determined simultaneously. In the next section, we therefore turn our attention to the factors driving those microstructure effects, for (i) the endogeneity problem is likely to be less severe then and (ii) the existing theories for their occurrence provide an alternative avenue to better understand the nature of the link between the forex market and official interventions.

²⁰The time series of daily aggregate absolute returns, omitted for economy of space, displays nearly identical dynamics.

²¹Market microstructure theory traditionally relates seasonal dynamics to inventory control, asymmetric information, and order processing; see O'Hara (1995) for a review. The monograph of Lyons (2001) analyzes many of these issues in the context of forex markets.

3.1. Event study methodology

Much of the recent debate in the literature (e.g., see the survey of Neely, 2005) is centered around whether the effects of infrequent interventions are permanent or transitory. Further, there is some empirical evidence that market participants tend to anticipate official interventions (e.g., Payne and Vitale, 2003 for the SNB). Thus, it is of interest to determine if exchange rate dynamics and market liquidity vary prior to SNB trades, how early currency dealers modify quotes and spreads in response to expectations of future SNB transactions, and how persistent these changes are over time. For that purpose, we use a basic event study methodology. Indeed, according to Fatum and Hutchison (2003, p. 390), “an event study framework is better suited to the study of sporadic and intense periods of official intervention, juxtaposed with continuously changing exchange rates [as in Figure 1a], than standard time-series studies” whose focus is exclusively on the contemporaneous impact of the intervention (e.g., Humpage, 1984; Dominguez and Frankel, 1993b).

A preliminary examination of our data reveals the presence of daily seasonality and long-term trends in the dynamics of our variables of interest (e.g., see Figs. 1a–f) which, if ignored, may bias the analysis. Hence, we specify, for each X_t and all events of type h , the regression

$$X_t = \alpha + \sum_{l=1}^2 \gamma_l X_{t-l} + \sum_{j=-8}^8 \delta_j I_t(j, h) + \sum_{i=1}^4 \psi_i D_t(i) + \sum_{k=1986}^{1997} \vartheta_k Y_t(k) + \varepsilon_t, \quad (2)$$

where $I_t(j, h)$ is an unsigned dummy equal to 1 in day t if during day $t + j$ the SNB executes a transaction of type h , and equal to zero otherwise, and $h = I, I > 0, I < 0, C, C > 0, C < 0$, or $I \& C$. The use of unsigned dummies allows for a potentially asymmetric impact of SNB purchases and sales of USD on any X_t . Nonetheless, in the special case of $X_t = r_t$ and $h = I, C$, or $I \& C$, we substitute the regressor $I_t(j, h)$ with the signed dummy $I_t^*(j, h)$ equal to 1 (−1) if the SNB executes a purchase (sale) of USD of type h during day $t + j$, and equal to zero otherwise. This is necessary to prevent the estimation of Eq. (2) from averaging across effects of opposite sign on currency returns. For $i = 1$ (Monday), ..., 4 (Thursday), $D_t(i)$ is a “day-of-the-week” dummy, while $Y_t(k)$ is a “year” dummy, for $k = 1986, \dots, 1997$. Eq. (2) also includes lags of X_t of order 1 and 2 to control for autocorrelation in the dependent variables.

We estimate this regression by OLS and evaluate the statistical significance of the coefficients' estimates with Newey–West standard errors to correct for heteroskedasticity and serial correlation. We interpret these estimates as follows. If $j > 0$, the coefficient δ_j on $I_t(j, h)$ (or $I_t^*(j, h)$) is a measure of *anticipation*, i.e., of the impact of the action of type h on X_t before that action actually occurs at time $t + j$. If $j = 0$, the coefficient δ_0 on $I_t(0, h)$ (or $I_t^*(0, h)$) is a proxy for the *contemporaneous* impact of the event of type h on X_t . Finally, if $j < 0$, the coefficient δ_j on $I_t(j, h)$ (or $I_t^*(j, h)$) is a measure of *persistence*, i.e., of the impact of the action of type h on X_t after that action has already occurred at time $t + j$.²² Hence, successive sums $\sum_{j=-w}^h$ of the dummy coefficients of this regression can be interpreted as measures of the cumulative impact of action h on the corresponding variable up to day

²²Accordingly, the specification of Eq. (2) controls for the possibility of partial anticipation of SNB actions and their clustering around the same time, since it measures the effect of a type h trade on X_t at any date $t + j$ after accounting for the occurrence of any other type h trade before or after $t + j$.

$t - w$. Thus, if, for example, $h = I$, $X_t = S_t$, and $w > 0$ ($w < 0$), then $\hat{\xi}_{-w}^h = \sum_{j=w}^8 \hat{\delta}_j$ is an estimate of the cumulative impact of official SNB interventions on the absolute spread up to $|w|$ days before (after) interventions of type I occur.

The event study methodology of Eq. (2) provides us with a preliminary picture of the relationship between SNB interventions (and their effectiveness) and CHFUSD market conditions without explicitly modeling the underlying data generation process.²³ Nonetheless, before discussing its results, it is important to emphasize two serious limitations of this empirical strategy.²⁴ First, Eq. (2) may produce biased estimates, since any Central Bank (including the SNB) is likely to intervene in response to observed exchange rate movements (r_t) and/or currency volatility ($|r_t|$ and r_t^2). The resulting endogeneity problem could be addressed by explicitly modeling the SNB's reaction function with instruments unrelated to CHFUSD fluctuations. Unfortunately, such instruments are extremely difficult to find because Central Bank policies are typically driven by the same set of fundamentals affecting exchange rates (Neely, 2005). The SNB makes no exception. Alternatively, Humpage and Osterberg (1992) and Fatum and Hutchison (2003) argue that the cumulative effect of official interventions over a sufficiently large window around each event date t may provide the most appropriate measure of its impact on exchange rate dynamics and so attenuate endogeneity biases in the estimation of Eq. (2). We follow the latter route and consider a window of 16 trading days around each aggregate daily SNB transaction.²⁵ Another feature of our database may also attenuate the endogeneity bias in the estimation of the contemporaneous impact coefficient δ_0 . Many intraday SNB interventions in our sample are in fact not only simultaneous (81% of them within a one hour interval) but also often executed in the early morning (42% of those before 10 a.m. GMT). The daily aggregates X_t are instead computed over the entire trading day, hence limiting their simultaneity with the intervention event.²⁶

Second, our event study methodology does not explicitly control for the effect of potentially important economic and financial aggregates—and the arrival of news about them—on the market for CHFUSD. However, the inclusion of year dummies in Eq. (2) accounts for potential temporal instability in the estimated parameters $\hat{\delta}_j$ due to time-varying macroeconomic conditions or changes in policies. We conduct a further robustness

²³The latter would require the specification of a full structural model of the simultaneous determination of exchange rates and intervention operations. This is a challenging task, since “no straightforward and empirically implementable model exists” to isolate the impact of unexpected interventions on currency returns (Payne and Vitale, 2003, p. 336).

²⁴Fatum and Hutchison (2003) and Neely (2005) discuss these issues in greater detail. A third potential limitation stems from the omission of (possibly simultaneous) intervention activity of other Central Banks among the regressors in Eq. (2). This omission is, however, less likely to bias our results since, over our sample period, (i) all SNB interventions in our sample are coordinated with either the Federal Reserve, the Bundesbank, or both, (ii) those Central banks “intervened in the same direction” as the SNB, and (iii) the SNB “presumably was the only Central Bank intervening” in the CHFUSD market (Fischer and Zurlinden, 1999, pp. 669–670). Many studies use Reuters news reports of the activity of G-7 Central Banks as control variables. This data, whose accuracy has been questioned (Osterberg and Wetmore Humes, 1993, 1995; Fischer, 2003), is unavailable to us.

²⁵The results below are not meaningfully affected by bigger or smaller event windows. This choice is also unlikely to induce serious specification errors (such as those mentioned by Humpage, 1999), as long as the SNB's policy horizon is longer than the selected event window, as is suggested by historical accounts of SNB's monetary policy over our sample period (e.g., Rich, 1997; Peytrignet, 1999).

²⁶As a further robustness check, we estimate Eq. (2) separately for days in which the first SNB transaction occurs in the morning (before noon) or in the afternoon and find, in both cases, qualitatively similar results to those presented next.

test by augmenting Eq. (2) with two additional variables proxying for changes in the monetary policy of the SNB and the Federal Reserve. According to [Peytrignet \(1999\)](#), as early as 1975 the SNB developed and pursued intermediate monetary targets consistent with its ultimate goal, domestic price stability. Over our sample period, the SNB targeted the domestic adjusted monetary base (AMB) between 1986 and 1989, and the seasonally adjusted monetary base (SAMB) afterward. We measure the fluctuations in SNB's monetary policy with smb_t , a time series of monthly log changes in either AMB or SAMB for the corresponding interval. Official changes in U.S. short-term interest rates are the most likely U.S. economic variable systematically related to CHFUSD fluctuations. We define dF_t as the time series of Federal Funds official rate changes.²⁷ Nonetheless, the inclusion of both smb_t and dF_t in Eq. (2) does not meaningfully affect the inference that follows.²⁸

3.2. SNB trades and market conditions

We estimate Eq. (2) for three types of official interventions (I , $I > 0$, and $I < 0$), for $I \& C$, and for three types of customer transactions (C , $C > 0$, and $C < 0$). Evidence from the set of events in $I \& C$ should reinforce the results for $h = I > 0$, since all official transactions there recorded are dollar purchases as well. We start by reporting in [Table 3](#) estimates of the contemporaneous impact coefficient δ_0 in Eq. (2) for each of the variables of interest.

The most striking result is that, after controlling for its short- and long-term trends, exchange rate volatility—as measured by absolute returns $|r_t|$ and realized conditional variation r_t^2 —increases following both official purchases and sales of USD on behalf of the SNB. No statistically significant change in market volatility is observed in the control sample made of ex post uninformative customer transactions. Hence, only potentially informative SNB trades increase the contemporaneous dispersion of intraday currency returns, regardless of their direction. Aggregate returns in intervention days, free of weekday and yearly patterns, are consistent with the direction of the corresponding SNB intervention. The CHF is, on average, weaker in days when the SNB buys USD and stronger in days when dollars are sold. Nonetheless, these excess returns are not significantly different from zero at any conventional level.²⁹

As pointed out by [Dominguez \(2003\)](#), Central Banks rarely offer precise information regarding the objectives of their official interventions or their policy horizons, and the SNB makes no exception. Moreover, market participants' perception of these objectives may crucially affect the impact of intervention on the exchange rate. Thus, the task of evaluating its effectiveness is daunting. Yet, the results of [Table 3](#) indicate that the SNB is unable to induce same-day directional moves to the Swiss Franc or to “calm disorderly

²⁷Although the Federal Open Market Committee (FOMC) meets 120 times over our sample period, the SNB intervenes on the same day when $dF_t \neq 0$ on only three occasions; on two of those it sells USD while the Federal Reserve either cuts or raises its key interest rate.

²⁸For instance, the coefficients for smb_t and dF_t from the estimation of the amended Eq. (2) for $X_t = r_t$ are statistically insignificant, and all the resulting $\hat{\zeta}_{-w}^h$ virtually identical to those from its original formulation. These results are not reported here but are available on request. Recent studies of G-3 interventions (e.g., [Dominguez, 2003, 2006](#)) use Reuters newswire reports of major economic events as control variables. This data is, to our knowledge, unavailable for the CHFUSD market.

²⁹The coefficient $\hat{\delta}_0$ is instead negative and significant when $h = C > 0$. This suggests that the SNB purchases dollars to replenish its reserves in days when the CHF is strong, consistent with the wealth-preservation motives modeled in [Pasquariello \(2005\)](#).

Table 3
Contemporaneous impact estimates
This table reports OLS estimates for the parameter δ_0 in the regression

$$X_t = \alpha + \sum_{l=1}^2 \gamma_l X_{t-l} + \sum_{j=-8}^8 \delta_j I_t(j, h) + \sum_{i=1}^4 \psi_i D_t(i) + \sum_{k=1986}^{1997} \vartheta_k Y_t(k) + \varepsilon_t \tag{2}$$

for each variable X_t defined in Section 3 over the interval February 3, 1986–December 31, 1998 (3,352 observations). $\hat{\delta}_0$ measures the impact of event $h = I, I \geq 0, C, C \geq 0$, or $I \& C$ on X after controlling for weekday seasonality (day dummies $D_t(i)$) and long-term trends (year dummies $Y_t(k)$). $I_t(j, h) = 1$ if a trade of type h occurs in day $t + j$, and zero otherwise. The t -statistics for $\hat{\delta}_0$ are computed from Newey–West standard errors. R_a^2 is the adjusted R^2 . A “^” indicates we replace $I_t(j, h)$ with $I_t^*(j, h) = 1$ (–1) if a USD purchase (sale) of type h occurred in day $t + j$, and zero otherwise. A “*” indicates significance at the 10% level.

X_t	$\hat{\delta}_0$ for different event types h						
	I	$I > 0$	$I < 0$	C	$C > 0$	$C < 0$	$I \& C$
r_t	0.163%	0.216%	–0.158%	–0.081%*	–0.107%*	0.154%	0.127%
t -stat	1.55	0.83	–1.40	–1.93	–2.39	0.63	0.37
R_a^2	1.42%^	0.68%	1.18%	0.72%^	1.40%	1.01%	1.05%^
$ r_t $	0.0502*	0.0965*	0.0373*	0.0001	–0.0009	0.0263	0.0390*
t -stat	4.93	3.03	3.99	0.01	–0.12	0.65	1.99
R_a^2	73.08%	73.11%	73.00%	73.08%	73.10%	72.99%	73.01%
r_t^2	0.00005*	0.00009*	0.00004*	3.7E-6	3.4E-6	8.0E-6	0.00006*
t -stat	4.88	3.17	4.69	0.61	0.55	0.29	2.38
R_a^2	64.85%	65.04%	64.69%	64.74%	64.74%	64.71%	64.89%
S_t	0.0432	–0.2470	0.1459*	0.0708	0.0787	–0.1216	0.8118*
t -stat	0.40	–0.87	1.67	1.37	1.47	–1.63	1.88
R_a^2	65.34%	65.51%	65.44%	65.42%	65.42%	65.24%	65.71%
s_t	–1.6E-6%	–0.002%	0.0008%	0.0007%*	0.0008%*	–0.0009%*	0.0070%*
t -stat	–0.00	–0.67	1.31	2.18	2.30	–2.09	2.05
R_a^2	64.46%	64.89%	64.59%	64.58%	64.59%	64.33%	65.27%
d_t	–42.76*	–82.00	–35.68*	–31.45*	–32.02*	–17.17*	–103.0
t -stat	–2.20	–1.28	–1.81	–2.44	–2.43	–2.14	–1.05
R_a^2	1.43%	3.39%	1.23%	1.23%	1.28%	0.51%	2.91%
f_t	102.5*	148.4*	91.27*	–0.36	–7.52	300.1*	58.09
t -stat	2.53	2.24	1.78	–0.01	–0.30	2.71	0.87
R_a^2	79.42%	79.39%	79.41%	79.54%	79.54%	79.41%	79.39%

markets,” at least in the very short run. Some of these actions have, however, a statistically significant impact on market liquidity and transaction costs. More quotes ($\hat{\delta}_0 = 103$ for f_t) are posted more frequently ($\hat{\delta}_0 = -43$ seconds for d_t) on the Reuters terminals during SNB interventions. The mean absolute spread increases by 0.146 pips when the SNB sells USD; that increase is even higher (0.812 pips) when the SNB accompanies CHF sales with customer transactions of the same sign ($h = I \& C$). These spread changes are economically significant as well. Using one-half of the mean daily CHFUSD turnover for 1998 (as in [Naranjo and Nimalendran, 2000](#)), we estimate that annualized round-trip transaction costs increase on average by almost \$150 million when $h = I < 0$ and by over \$815 million when

$h = I \& C$. These estimates are not negligible, especially in a highly efficient market like the one for CHFUSD. Assuming that the market's order flow is relatively insensitive to a change in spread of about one pip, they represent a net gain for the dealers, hence a net loss for investors.

The analysis of the impulse-response functions $\hat{\xi}_{-w}^h$, plotted in Fig. 2 (together with 90% confidence intervals for I and C), sheds further light on the mechanics and implications of SNB trades. Overall, our evidence suggests that SNB interventions have an asymmetric impact on the process of price formation in the CHFUSD market: official dollar purchases ($I > 0$ and $I \& C$) induce the biggest reaction in returns, return volatility, trading intensity, and transaction costs. Over our sample period, the SNB purchases USD (CHF) in response to a steady appreciation (depreciation) of about 1% in the domestic currency. On average, the market does not anticipate the incoming interventions: estimates of $\hat{\xi}_{-w}^h$ for r_t (in the left panel of Fig. 2a) move in the direction of the intervention only starting with $\hat{\delta}_0$. Nonetheless, the market reaction to these trades is important and persistent: The Swiss Franc weakens after a USD purchase or strengthens after a USD sale for up to five days following the official intervention. Thus, the SNB is successful in slowing or reversing a trend in the CHFUSD, even though its transactions are generally smaller than typical forex trades. Fig. 2a also suggests that any new information resulting from those interventions does not immediately disseminate to all market participants.

That information might play an important role in explaining these findings is again confirmed by the analysis of our control sample made of ex post uninformative customer transactions (in the right panel of Fig. 2a). If imperfect asset substitutability at the market or dealer level is relevant to the effectiveness of Central Bank interventions (as argued, for example, by Evans and Lyons, 2003), even customer transactions should affect dealers' inventories, interdealer order flow, and eventually currency returns through market participants' efforts at rebalancing their portfolios. Albeit comparable in size to intervention trades, their cumulative impact on midquote returns is instead economically negligible. This is consistent with the intraday evidence in Payne and Vitale (2003).

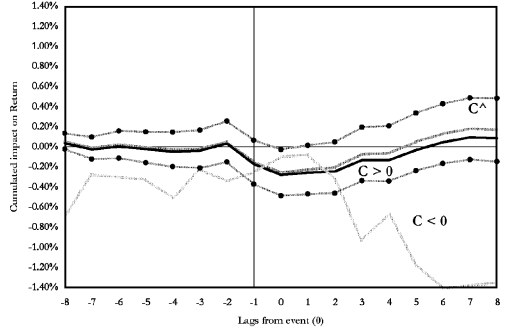
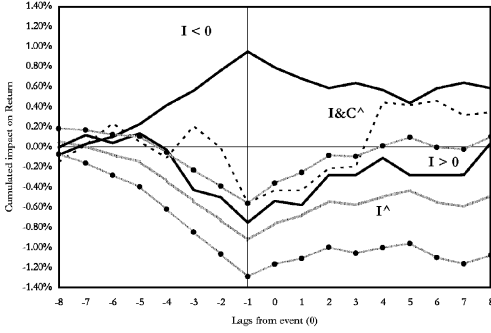
In the left panels of Figures 2b ($|r_t|$) and 2c (r_t^2), within-day exchange rate volatility appears to pick up as soon as the market learns of an incoming intervention.³⁰ Uncertainty surrounding scope, time horizon, and motives of those interventions induces increased market uncertainty and more reluctance to advertise new quotes up to three days before their occurrence.³¹ However, in response to clearer anticipation of future SNB activity, in the days immediately preceding the event dealers update their posted quotes more frequently (d_t declines in the left panel of Fig. 2f)³² and market more aggressively their

³⁰The dynamics of $\hat{\xi}_{-w}^h$ for $|r_t|$ and r_t^2 cannot be explained by a drift induced by the intervention to the underlying exchange rate process. In fact, when we estimate Eq. (2) for a measure of dispersion of tick-by-tick returns from their daily intraday mean, the standard deviation of $r_{t,h}$ over day t (i.e., in arrival time), the resulting impact dynamics (not reported here) are similar to those in Figs. 2b and c.

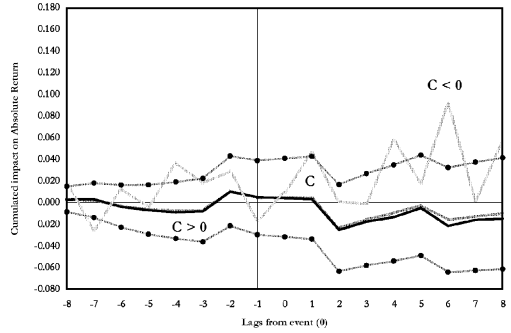
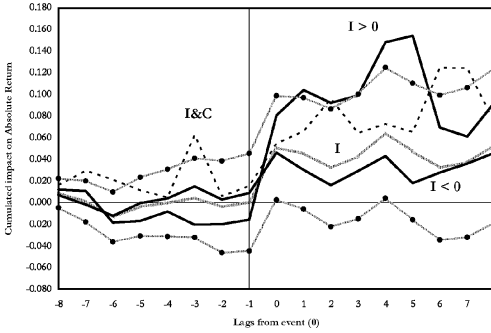
³¹As a further robustness test, we also describe the evolution of daily CHFUSD returns and return volatility with a standard GARCH(1,1) model augmented with the intervention dummies described in Section 3.1. The profiles of the resulting impulse-response functions $\hat{\xi}_{-w}^h$, available on request, are nevertheless similar to those presented in Figs. 2a–c.

³²For robustness, we also estimate a proportional hazard model of the effect of the various regressors in Eq. (2) on the average length of time between two consecutive new quotes posted on the Reuters screens within a day for each event h . The resulting estimated coefficients are of more arduous interpretation than $\hat{\delta}_j$; yet, their cumulative sums (available on request) are qualitatively similar to those reported in Fig. 2f.

a



b



c

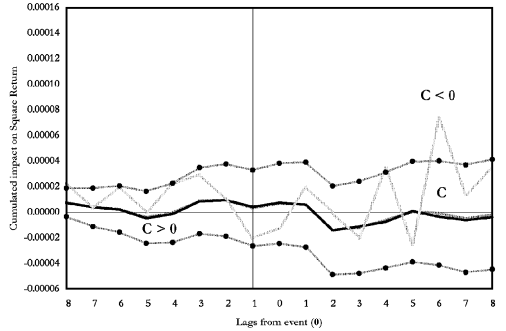
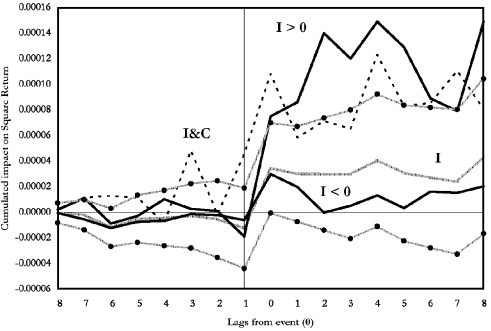


Fig. 2. Cumulative impact of interventions and customer transactions. These figures plot cumulative sums $\hat{\xi}$ of OLS estimates of the dummy coefficients $\hat{\delta}$ in the regression

$$X_t = \alpha + \sum_{l=1}^2 \gamma_l X_{t-l} + \sum_{j=-8}^8 \delta_j I_t(j, h) + \sum_{i=1}^4 \psi_i D_t(i) + \sum_{k=1986}^{1997} \vartheta_k Y_t(k) + \varepsilon_t \quad (2)$$

for each variable X_t defined in Section 3 and each event type $h = I, I \geq 0, C, C \geq 0$, or $I \& C$. If $w > 0$ ($w < 0$), then $\hat{\xi}_{-w}^h = \sum_{j=-w}^8 \hat{\delta}_j$ is the estimated cumulative impact of trades h on X up to $|w|$ days before (after) they occur. A “ \wedge ” indicates that we replace $I_t(j, h)$ in Eq. (2) with the signed event dummy $I_t^*(j, h)$. The dotted lines trace 90% confidence intervals for the cumulative impact of trades of type $h = I$ and C . (a) Return r_t ; (b) absolute return $|r_t|$; (c) square return r_t^2 ; (d) spread S_t ; (e) logarithmic spread s_t ; (f) duration d_t ; and (g) frequency f_t .

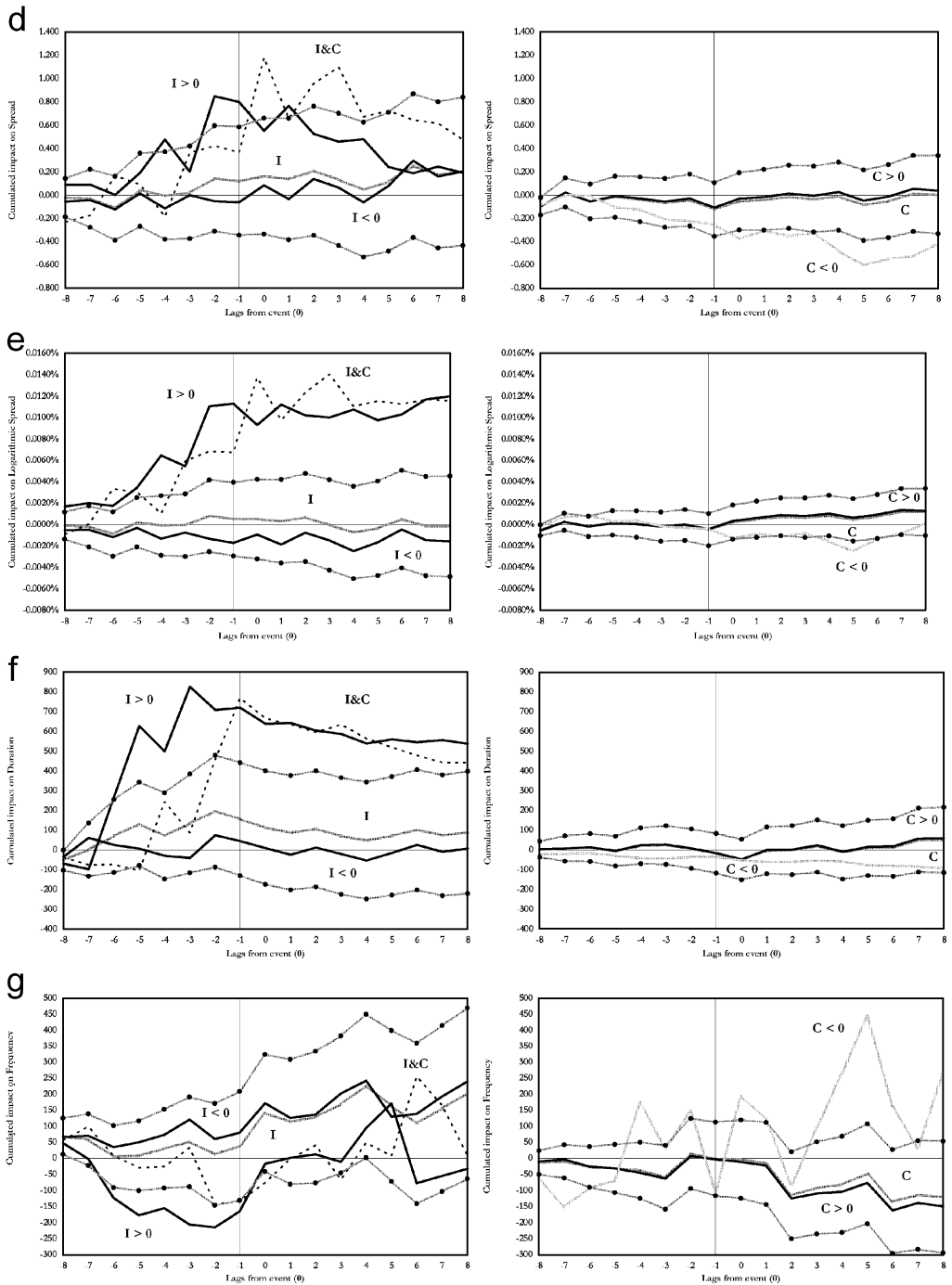


Fig. 2. (Continued)

availability to trade by posting more quotes (f_t increases in the left panel of Fig. 2g).³³ Nonetheless, contrary to the evidence reported by Dominguez (2006) for G-3 interventions, the arrival of SNB trades does little to reduce the dispersion of beliefs among market participants: Return volatility actually increases sharply and stays high well beyond the event date. Again, uninformative customer transactions have no impact on $|r_t|$, r_t^2 , d_t and f_t , as shown in the right panels of Figs. 2b, c, f, and g.

Not only do dealers revise indicative bid and ask prices on the FXXF page more often, but they also widen posted spreads almost simultaneously with the increase in return volatility. Absolute and proportional spreads (in the left panels of Figs. 2d and e) do not return to previous levels even 8 days after the SNB trades were executed.³⁴ Hence, the effectiveness of SNB interventions is accompanied not only by greater fluctuations in the exchange rate but also by higher transaction costs borne by investors for a relatively long period of time. This long-lasting surge in volatility and spreads could be the result of protracted uncertainty and disagreement over sign, size, and timing of future interventions. Indeed, slow resolution of uncertainty and misinformation is consistent with the post-event drift in returns observed in Fig. 2a.³⁵ Risk-averse dealers would then react by widening their spreads (as in Stoll, 1978). Secrecy is also often invoked to explain greater currency volatility in proximity of interventions (e.g., Dominguez, 1998). Similarly, Naranjo and Nimalendran (2000) argue that uncertainty surrounding the unexpected component of Central Bank transactions may induce dealers to increase their spreads because of adverse selection considerations. However, the evidence in Table 3 and Fig. 2 does not easily reconcile with these explanations, since CHFUSD dealers know when the SNB hits their quotes, and the nature of its actions is revealed to them immediately afterward and quickly divulged to the rest of the market.³⁶

As in Table 3, bid–ask spreads (S_t and s_t), frequency (f_t), and duration (d_t) of posted quotes (in the right panels of Figs. 2d–g) are not affected by signed or unsigned customer transactions. This corroborates our (still preliminary) assertion that inventory considerations play only a secondary role in explaining the impact of SNB trades on the process of price formation in the CHFUSD market, in particular on the dynamics of market liquidity

³³Given the discrete nature of the frequency variable f_t , we also estimate a Poisson regression model for the number of newly posted quotes per day using the same regressors as those in Eq. (2). The dynamics of the resulting cumulative parameter estimates (available on request), albeit more difficult to interpret, are nearly identical to those displayed in Fig. 2g.

³⁴The average daily bid–ask spread series defined in Section 2.2 (and plotted in Fig. 1c), $S_t = f_t^{-1} \sum_{n=1}^{f_t} S_{t_n}$, does not display the clustering that instead characterizes its intraday realizations (e.g., see Pasquariello, 2003). As a robustness check, we also compute an alternative, discrete daily spread series, S_t^* , given by the median of the corresponding observed intraday spreads S_{t_n} . We then estimate an ordered probit model for S_t^* whose independent variables are the same as those in Eq. (2). The resulting impulse-response functions, available on request, are nearly identical to those plotted in Fig. 2d.

³⁵Guembel and Sussman (2001) offer an alternative, intriguing interpretation of Fig. 2. They show that reducing exchange rate volatility and deterring speculation may be mutually incompatible objectives. This is the case when the Central Bank can curb speculators' profits only at the cost of increasing the currency's responsiveness to order flow, hence the variance of intraday currency returns. The patterns in Figs. 2a–c would then arise from the SNB's optimal resolution of this trade-off. Unfortunately, without further evidence on the intensity of speculative activity on the Swiss Franc, this argument cannot be substantiated.

³⁶More generally, Dominguez (2003) observes that although interventions (like any other forex trade) are officially anonymous, most Central Banks develop relationships with dealers allowing to be identified as a counterparty.

and transaction costs. More work to clarify the nature of these effects is clearly warranted. We do so in Section 4.

3.3. Size, trend, and expectations

We have so far classified SNB trades merely according to their sign. Whether an intervention is to buy or sell the domestic currency is, however, not the only distinguishing characteristic which may affect its impact on the forex markets. In this section, we focus on three additional features of these transactions and assess their relative significance in explaining the impact of SNB interventions on the CHFUSD market.

The first feature is *size*. A number of theoretical studies find larger interventions more likely to influence currency returns, return volatility, and market liquidity because they represent more expensive signals (Bhattacharya and Weller, 1997; Vitale, 1999), are “hot potatoes” to be passed from one dealer to the other (Evans and Lyons, 2003), or induce greater drifts in the inventories of competing dealers (Pasquariello, 2005). The second feature is *market momentum*. Central Banks often trade currencies to support, resist, or reverse existing trends in key exchange rates.³⁷ Conventionally, interventions in the direction of a trend are known as *chasing the trend*, while interventions challenging it are known as *leaning against the wind*. Yet, more evidence has been found for the latter than for the former.³⁸

Extant empirical research analyzes the relevance of these considerations for the effectiveness of official interventions.³⁹ It nonetheless remains to establish if both types of interventions have a differential impact on the process of price formation in the forex market as a whole. We do so by first separating SNB daily interventions based on their relative magnitude or consistency with current market momentum. Specifically, we classify a cumulative SNB intervention in day t , I_t , as small (big) if $|I_t| \leq (>) \$50$ million, its median over the entire sample. According to this criterion, 57 SNB interventions are small (I_{small}) and 29 are big (I_{big}). I_{small} are more numerous than I_{big} because many such trades are of median size; about 80% of each group are USD sales. Along the lines of Payne and Vitale (2003), we define I_t as chasing the trend (leaning against the wind) if $\text{sign}(I_t) = (\neq) \text{sign}(r_{t-1} + r_{t-2})$. As a result, only 22 interventions (16 of which are CHF purchases) are labeled as chasing the trend (I_{trend}) and 64 (12 of which are CHF sales) as leaning against the wind (I_{wind}).⁴⁰ The larger number of the latter trades in our sample is consistent with historical accounts of the SNB’s currency policy as pragmatically responding to unanticipated, momentous exchange rate shocks between 1986 and 1995 (e.g., Rich, 1997; Peytrignet, 1999).

³⁷For instance, Dominguez and Frankel (1993b) and Lewis (1995) show that most interventions attempt to keep domestic currencies close to some target levels. Dominguez (2003) argues that calming otherwise disorderly markets is also a likely priority of Central Banks.

³⁸For example, Central Banks often buy USD while the dollar is depreciating (Taylor, 1982) or despite expectations of lower U.S. interest rates, i.e., inconsistently with fundamentals (Lewis, 1995; Kaminsky and Lewis, 1996). Edison (1993) finds strong evidence of interventions leaning against the wind, but only weaker evidence of interventions chasing the trend to correct currency misalignments.

³⁹Recent examples include Fatum and Hutchison (2003), Payne and Vitale (2003), and Kearns and Rigobon (2005).

⁴⁰We obtain identical classifications when using one- or three-day intervals preceding the intervention events.

Table 4
Additional contemporaneous impact estimates
This table reports standard OLS estimates for the parameter δ_0 in the regression

$$X_t = \alpha + \sum_{l=1}^2 \gamma_l X_{t-l} + \sum_{j=-8}^8 \delta_j I_t(j, h) + \sum_{i=1}^4 \psi_i D_t(i) + \sum_{k=1986}^{1997} \vartheta_k Y_t(k) + \varepsilon_t \tag{2}$$

for each variable X_t defined in Section 3. $\hat{\delta}_0$ measures the impact of the events $h = I, I_{\text{small}}, I_{\text{big}}, I_{\text{trend}}$, and I_{wind} (defined in Section 3.3) on X , after controlling for weekday seasonality (with day dummies $D_t(i)$) and long-term trends (with year dummies $Y_t(k)$). The unsigned dummy $I_t(j, h)$ and the signed dummy $I_t^*(j, h)$ have been described in the notes to Table 3. The t -statistics for $\hat{\delta}_0$ are computed from Newey–West standard errors. R_a^2 is the adjusted R^2 . A “^” indicates that we replace $I_t(j, h)$ with $I_t^*(j, h)$ for the event type h . A “*” indicates significance at the 10% level.

$\hat{\delta}_0$ for different event types h					
	I	I_{small}	I_{big}	I_{trend}	I_{wind}
r_t	0.163%	0.200%	0.028%	0.075%	0.105%
t -stat	1.55	1.55	0.20	0.37	0.95
R_a^2	1.42%^ [^]	1.23%^ [^]	0.68%^ [^]	1.25%^ [^]	1.92%^ [^]
$ r_t $	0.0502*	0.0495*	0.0471*	0.0235	0.0584*
t -stat	4.93	5.16	2.22	1.35	4.79
R_a^2	73.08%	73.05%	73.10%	73.00%	73.10%
r_t^2	0.00005*	0.00004*	0.00006*	0.00004*	0.00005*
t -stat	4.88	4.02	3.28	2.36	4.23
R_a^2	64.85%	64.77%	64.76%	64.75%	64.77%
S_t	0.0432	−0.0389	0.2495	−0.0611	0.0592
t -stat	0.40	−0.36	1.47	−0.75	0.51
R_a^2	65.34%	65.37%	65.46%	65.37%	65.32%
s_t	−1.6E-6%	−0.0007%	0.0017%	−0.0007%	0.0001%
t -stat	−0.00	−0.80	1.51	−1.12	0.11
R_a^2	64.46%	64.53%	64.61%	64.54%	64.44%
d_t	−42.76*	−37.30*	−40.18*	−4.23	−45.61*
t -stat	−2.20	−1.96	−1.75	−0.26	−2.24
R_a^2	1.43%	1.69%	1.27%	1.88%	1.59%
f_t	102.5*	164.1*	−32.12	6.28	141.5*
t -stat	2.53	3.67	−0.52	0.08	3.12
R_a^2	79.42%	79.46%	79.49%	79.40%	79.43%

We then re-estimate Eq. (2) for the new intervention types $h = I_{\text{small}}, I_{\text{big}}, I_{\text{trend}}$, and I_{wind} , to measure their contemporaneous effect on each variable X_t ($\hat{\delta}_0$ in Table 4) and their cumulative impact on a subset of them ($\hat{\xi}_{-w}^h$ for r_t, r_t^2, S_t , and d_t in Fig. 3).⁴¹ Interventions that are small and leaning against the wind have the largest marginal, and

⁴¹Roughly 20% of each of those groupings is made of CHF sales, consistent with the original sample I , thus making a comparison of these estimates across old and new intervention types reasonable. Impulse-response functions for $|r_t|, s_t$, and f_t , not reported here for economy of space, are qualitatively similar to those for r_t^2, S_t , and d_t , respectively.

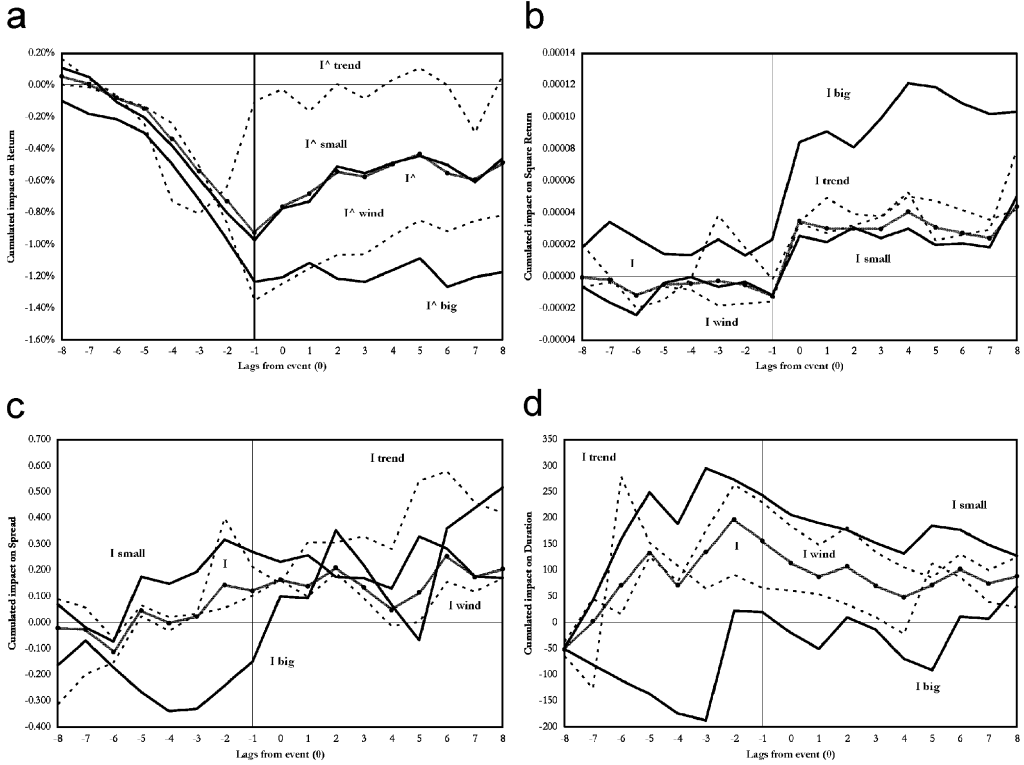


Fig. 3. Additional cumulative impact of interventions. These figures plot cumulative sums $\hat{\zeta}$ of OLS estimates of the dummy coefficients $\hat{\delta}$ in the regression

$$X_t = \alpha + \sum_{l=1}^2 \gamma_l X_{t-l} + \sum_{j=-8}^8 \delta_j I_t(j, h) + \sum_{i=1}^4 \psi_i D_t(i) + \sum_{k=1986}^{1997} \vartheta_k Y_t(k) + \varepsilon_t \quad (2)$$

for $X_t = r_t, r_t^2, S_t$, or d_t and each trade type $h = I$ (punctuated line), I_{small} and I_{big} for size (dark lines), and I_{trend} and I_{wind} for direction (dotted lines), defined in Section 3.3. If, for example, $h = I$ and $w > 0$ ($w < 0$), then $\hat{\zeta}_{-w}^h = \sum_{j=w}^8 \hat{\delta}_j$ is the estimated cumulative impact of official SNB interventions on X up to $|w|$ days before (after) they occur. A “ \wedge ” indicates that we replace $I_t(j, h)$ in Eq. (2) with the signed event dummy $I_t^*(j, h)$. (a) Return r_t ; (b) square return r_t^2 ; (c) spread S_t ; and (d) duration d_t .

the most persistent aggregate, impact on CHFUSD daily returns, but at the same time the smallest impact on market liquidity (Figs. 3c and d). Instead, according to Figs. 3a–d, big interventions are typically preceded by a significant appreciation of the Swiss Franc, have virtually no effect on it, yet appear to induce significant market instability and greater transaction costs. Cumulative return volatility and spread shocks are in fact among the largest when $h = I_{\text{big}}$. Interventions chasing the trend, i.e., reinforcing investors’ and dealers’ beliefs about the currency, affect only marginally the exchange rate, are almost completely reabsorbed one day after the event, and generate among the smallest shocks to daily volatility. Interestingly, I_{trend} actions are typically foreseen by the market at least two days before their occurrence. Hence, uninformed dealers may be able to recognize levels of CHFUSD around which trend-chasing SNB interventions become more likely and adjust

their quotes accordingly. This evidence contradicts recent studies suggesting that large official operations are more likely to successfully influence exchange rate levels (e.g., Fatum and Hutchison, 2003; Payne and Vitale, 2003); it is nonetheless consistent with the observation made by Rich (1997, p. 113) that over our sample period the SNB may have engaged in “inappropriate... response to such disturbances as unexpected exchange rate shocks,” so inducing high short-term currency volatility.

The third feature is *market expectations*. The market microstructure literature has long attempted to identify information and inventory control effects in the price impact of trades. In particular, it has long emphasized (since Hasbrouck, 1988) that private information from an observed trade can be inferred only from that trade’s unanticipated portion. This insight is consistent with theoretical studies of the signaling channel of intervention effectiveness (Bhattacharya and Weller, 1997; Vitale, 1999). More recently, the impact of interventions on market liquidity has also received attention. For instance, in Naranjo and Nimalendran (2000), the unexpected portion of official interventions widens the bid–ask spread via adverse selection; in Pasquariello (2005), uncertainty about the likelihood of future interventions makes it more difficult for dealers to clear the market. According to these views, only unexpected interventions should affect transaction costs as well.

Translating this insight into an empirical strategy is nonetheless challenging. The sporadic nature of the intervention activity and the secrecy of its timing make explicit, specific expectations about those official transactions generally unavailable. Some studies (e.g., Naranjo and Nimalendran, 2000) estimate residuals from policy reaction models to capture intervention surprises, yet these estimates are dependent on the selected model specification. In a seminal paper, Hasbrouck (1991) suggests a structure-free approach based on the estimation of vector autoregression (VAR) models of auto- and cross-correlations between trades, quote revisions, and spreads. We adapt this empirical strategy to our setting.⁴² Specifically, we model the potential interaction between the various facets of posted quote revisions (the variables X_t defined in Section 2.2) and signed aggregate daily SNB trades T_t by estimating the following bivariate VAR system

$$X_t = \alpha_1 + \sum_{l=1}^{20} a_l X_{t-l} + \sum_{l=0}^{20} b_l T_t + \sum_{i=1}^4 \psi_{1,i} D_t(i) + \sum_{k=1986}^{1997} \vartheta_{1,k} Y_t(k) + \varepsilon_{1,t}, \quad (3)$$

$$T_t = \alpha_2 + \sum_{l=1}^{20} c_l T_{t-l} + \sum_{l=0}^{20} d_l X_t + \sum_{i=1}^4 \psi_{2,i} D_t(i) + \sum_{k=1986}^{1997} \vartheta_{2,k} Y_t(k) + \varepsilon_{2,t} \quad (4)$$

for $T_t = I_t > 0$, $I_t < 0$, C_t , and $I_t^\& + C_t^\&$. This setting allows us to identify the permanent impact of the *unexpected* component of an SNB trade on the process of price formation in the CHFUSD market without explicitly modeling trade innovations but nevertheless explicitly accounting for their contemporaneous determination. Hence, the latter feature also mitigates the endogeneity bias affecting the event study methodology of Section 3.1.⁴³

We plot the impulse-response functions from the joint estimation of Eqs. (3) and (4) for $X_t = r_t$, r_t^2 , S_t , s_t , and f_t due to an initial *signed* trade shock of \$50 million (the median size

⁴²We thank Bruce Lehmann for suggesting this line of action to us.

⁴³The discussion in Section 3.1 motivates the bivariate VAR for $X_t = r_t$ or r_t^2 . The rationale behind the interaction between SNB trades and market liquidity is less obvious, but ensues from the observation in Fischer and Zurlinden (1999, p. 667) that “the SNB does not try to influence the market when trading is thin” over our sample period.

of signed intervention in Table 1) in Figs. 4a and c–f, respectively, as well as the impulse-response function for T_t due to a 1% initial CHFUSD return shock in Fig. 4b.⁴⁴ Unexpected official SNB dollar purchases (sales) stem from prolonged appreciations (depreciations) of the Swiss Franc (Fig. 4b), and lead to larger and more persistent trend-reversals (Fig. 4a) than those displayed in Fig. 2a. Interestingly, price adjustments to surprise interventions are not complete even 20 trading days after their execution, while the convergence of their impact on return volatility (Fig. 4c) is much more rapid (usually within a week). In Figs. 2d–g, SNB trades are preceded by wider spreads and longer delays between newly posted quotes. According to the model of Eqs. (3) and (4), this deterioration in market liquidity—when driven by unexpected SNB interventions—is only partially reversed afterward, the less so when following unexpected official USD sales ($I_t < 0$ in Figs. 4d–f). Finally, and consistent with the evidence in Fig. 2, customer transactions have no permanent impact on the CHFUSD market. Overall, these results indicate that, when unanticipated, SNB interventions have a more pronounced directional effect on the Swiss Franc, yet at the cost of greater volatility and transaction costs borne by investors.

4. Decomposing liquidity shocks

In the previous section, we examined the impact of SNB interventions on multiple dimensions of the process of price formation in the CHFUSD market, rather than just on subsets of them, as is common in the literature. In particular, we showed that the SNB is successful, on average, in reversing current market trends for the Swiss Franc, even when its interventions are small and especially when unexpected. However, regardless of their effectiveness, such interventions are generally accompanied by greater exchange rate volatility, wider absolute and proportional spreads, and more frequent updates of intraday indicative quotes. These changes are statistically and economically significant, often precede the actual intervention, and are protracted in time. In the control sample made of customer transactions, their cumulative impact on CHFUSD returns, return volatility, and market liquidity is instead negligible.

This evidence suggests that both the effectiveness of the SNB's intervention activity in the CHFUSD market and its implications for that currency's trading environment may be related to its perceived information content, rather than to portfolio balance considerations. Further insight may be gained into the nature of these effects by exploring the interaction between our variables of interest than by examining each of them in isolation, as in traditional, model-free event studies. We undertake this task in this section by focusing on bid–ask spread shocks in proximity of SNB interventions. The market microstructure literature develops in fact several theories of spread determination (surveyed in O'Hara, 1995) invoking information, inventory, risk, or liquidity considerations. Assessing the relevance of these arguments in explaining the impact of SNB interventions on transaction costs may therefore shed further light on the factors driving their impact on CHFUSD returns and return volatility.

⁴⁴As a robustness check, we estimate Eqs. (3) and (4) without contemporaneous interaction terms (i.e., imposing that $b_0 = d_0 = 0$), as well as after replacing the signed trades T_t with their indicator counterparts I_t (0, h), as in Hasbrouck (1991). In addition, we also estimate multivariate VARs for the interaction between our variables of interest X_t . All of the resulting impulse-response functions, available on request, are similar to those in Fig. 4.

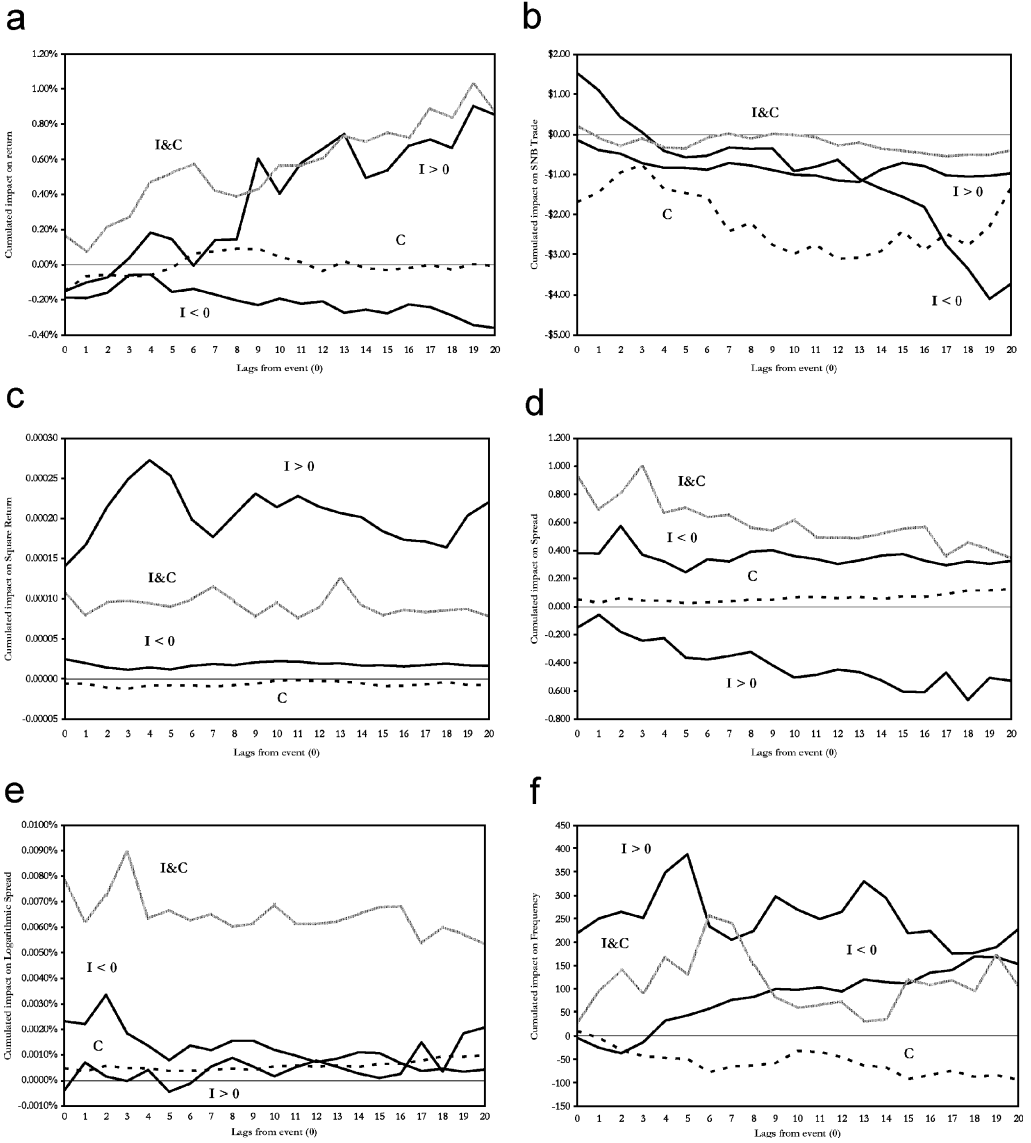


Fig. 4. Bivariate VAR: impulse-response functions. These figures plot SUR estimates of the cumulative revisions in X_t subsequent to an initial USD 50 million *signed* SNB trade $T_t = I_t > 0$, $I_t < 0$, C_t , or $I_t^\& + C_t^\& > 0$ implied by the bivariate VAR model

$$X_t = \alpha_1 + \sum_{l=1}^{20} a_l X_{t-l} + \sum_{i=0}^{20} b_i T_t + \sum_{i=1}^4 \psi_{1,i} D_t(i) + \sum_{k=1986}^{1997} \vartheta_{1,k} Y_t(k) + \varepsilon_{1,t}, \quad (3)$$

$$T_t = \alpha_2 + \sum_{l=1}^{20} c_l T_{t-l} + \sum_{l=0}^{20} d_l X_t + \sum_{i=1}^4 \psi_{2,i} D_t(i) + \sum_{k=1986}^{1997} \vartheta_{2,k} Y_t(k) + \varepsilon_{2,t} \quad (4)$$

for each variable X_t defined in Section 2.2. Specifically, (a) and (b) plot estimated impulse-response functions for both $X_t = r_t$ and T_t (for $\Delta r_t = 0.01$) while (c)–(f) plot estimated impulse-response functions for X_t from each bivariate VAR model with either $X_t = r_t^2$, S_t , s_t , or f_t , respectively. (a) Return r_t ; (b) intervention I_t ; (c) square return r_t^2 ; (d) spread S_t ; (e) logarithmic spread s_t ; and (f) frequency f_t .

Specifically, from this literature we identify three basic explanations for the impact of Central Bank interventions on bid–ask spreads in the currency market. The first one relies on the role of *information*. According to Peiers (1997) and Naranjo and Nimalendran (2000), official intervention is a source of information asymmetry among dealers and between dealers and the Central Bank, respectively. Both circumstances may in turn increase the adverse selection component of the dealers' posted exchange rate spread. Grossman and Miller (1988) suggest that, following the release of stabilizing information, transaction costs should decline. Alternatively, Stein (1987) emphasizes the destabilizing role of misinformation stemming from increasing information heterogeneity, which could then widen the prevailing bid–ask spread (as in Copeland and Friedman, 1987). Second, interventions may have a *liquidity* effect on the forex markets: Imperfect substitutability of otherwise identical assets denominated in different currencies may induce dealers to adjust quotes (as in Evans and Lyons, 2003) and spreads to clear the market. Moreover, interventions may push dealers' inventories away from optimal levels, inducing asymmetric revisions of bid and ask prices (Stoll, 1978; Amihud and Mendelson, 1980; Pasquariello, 2005). Finally, official interventions may signal more general shifts in the fundamental characteristics of the exchange rate, thus affecting exchange rate *volatility* (as in Figures 2b, 2c, 3b, and 4c), hence the spreads posted by risk-averse dealers. In the remainder of this study, we develop and estimate a reduced-form model of the relation between bid–ask spread shocks and information, liquidity, and volatility in proximity of SNB interventions.

4.1. The model

We focus on the observed changes in absolute spreads (ΔS_i) around SNB trades as a proxy for the CHFUSD market's ability to accommodate trades and news with the least impact on transaction costs.⁴⁵ In order to decompose those changes, we extend a model originally developed by Fedenia and Grammatikos (1992). We start by assuming that the absolute spread in proximity of an intervention i , S_i , is a function of two by-products of that trade, liquidity L_i and information I_i , i.e., $S_i = S_i(L_i, I_i)$, so that the resulting change in spread ΔS_i can be described as $\Delta S_i = (\partial S_i / \partial L_i) \Delta L_i + (\partial S_i / \partial I_i) \Delta I_i$.

As previously mentioned, information shocks might condition the dynamics of bid–ask spreads in two ways. First, the arrival of intervention information may affect exchange rate volatility, ΔV_i , and in turn the spread. Second, interventions may affect the degree of information heterogeneity among investors, H_i , hence the spread. Therefore, we impose that $I_i = I_i(\Delta V_i, H_i)$. This implies that $\Delta I_i = (\partial I_i / \partial \Delta V_i) \Delta(\Delta V_i) + (\partial I_i / \partial H_i) \Delta H_i$, which we substitute in the expression for ΔS_i to obtain

$$\Delta S_i = \frac{\partial S_i}{\partial L_i} \Delta L_i + \frac{\partial S_i}{\partial \Delta V_i} \Delta(\Delta V_i) + \frac{\partial S_i}{\partial H_i} \Delta H_i. \quad (5)$$

Eq. (5) decomposes observed spread changes around interventions into shocks to market liquidity (ΔL_i , e.g., due to inventory shocks), shifts in currency volatility ($\Delta(\Delta V_i)$), and changes in the dispersion of beliefs among market participants (ΔH_i). To make this expression operational, we need to measure both its shock variables and partial

⁴⁵Shocks to proportional spreads (Δs_i) are less adequate proxies for shifts in liquidity induced by SNB interventions, since these trades affect significantly cumulative midquote CHFUSD returns, hence the implicit denominator in s_i . This effect could then bias any inference on transaction costs based on the dynamics of Δs_i .

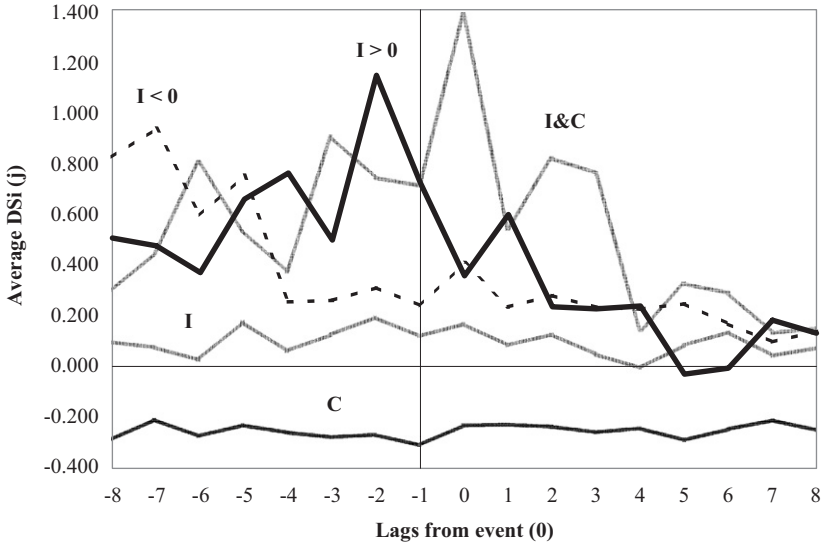


Fig. 5. Average spread shock measures over the event interval. This figure displays the average shocks to the absolute spread, $\Delta S_i(j) = S_i(j) - \bar{S}_i^b$, defined in Section 4.1, for each day of a 16-day window surrounding a SNB transaction of type h . These averages are computed over all such windows surrounding each day τ_i in the sample when the corresponding event of type h is observed. For instance, consider the i th event of type h in the sample, occurring on day τ_i . Then, $S_i(j)$ is the absolute spread observed in day $\tau_i + j$, while the corresponding benchmark \bar{S}_i^b is computed over the first 20 days preceding the third to last day before the event window $[\tau_i - 8, \tau_i + 8]$ that do not contain any past event of the same type. If we label such days with a “*” symbol, then $\bar{S}_i^b = \sum_{j=-30}^{-11} S_i(j)/20$. Hence, benchmarks may differ depending on the event type under study. We compute average spread shocks in correspondence with all SNB interventions ($h = I$), all official USD purchases ($h = I > 0$) and sales ($h = I < 0$), all customer transactions ($h = C$), and all event windows around days when transactions of both type $h = I$ and type $h = C$ (all of which are CHF sales) take place ($h = I \& C$).

derivatives. We start by estimating the aggregate spread shock on the i th intervention day (day τ_i) as $\Delta S_i = \bar{S}_i - \bar{S}_i^b$, where \bar{S}_i is the average absolute spread over the interval $[\tau_i - 8, \tau_i + 8]$, as in Eq. (2), and \bar{S}_i^b is a benchmark pre-intervention spread.⁴⁶ To further control for event endogeneity and any anticipation or persistence of effects of SNB interventions, we define (and later decompose) an additional spread shock variable, $\Delta S_i(j) = S_i(j) - \bar{S}_i^b$, for each of the days $j \in [-8, 8]$ surrounding the event date τ_i . Fig. 5 plots averages of those shock measures ($\overline{\Delta S_i(j)}$) for each lead and lag j from the event date τ_i when the event is of type $h = I, I > 0, I < 0, C$, and $I \& C$. The dynamics of Figs. 2d and 5 are strikingly similar: Consistent with Fig. 2d, shocks to the absolute spread $S_i(j)$ (except around customer transactions) are positive, large, and increasing prior to official SNB trades—especially USD purchases—but decline steadily afterward.

⁴⁶To mitigate any potential bias induced by event clustering in the sample, we compute \bar{S}_i^b as the average spread over the first 20 days preceding the third to last day before the event window $[\tau_i - 8, \tau_i + 8]$ that do not contain any other past corresponding event-window day. If we label such days with a “*” symbol, then $\bar{S}_i^b = \sum_{j=-30}^{-11} S_i(j)/20$, where $S_i(j)$ is the absolute spread observed at $\tau_i + j$. In the analysis that follows, alternative intervals of either 10 or 30 days preceding the third to last day before the event window $[\tau_i - 8, \tau_i + 8]$ lead to the same inference.

We then focus on the variables on the right side of Eq. (5). Amihud and Mendelson (1980) and Pasquariello (2005) provide a rationale for interventions to affect bid–ask spreads through their impact on dealers' inventories; similarly, in the equilibrium model of Cohen et al. (1981), spreads are inversely related to liquidity ($\partial S_i / \partial L_i < 0$) because of transaction costs, but at a decreasing rate ($\lim_{L_i \rightarrow \infty} \partial S_i / \partial L_i = 0$). For simplicity, we impose that $\partial S_i / \partial L_i \approx \beta_i / L_i$ (with $\beta_i < 0$) and that the benchmark \bar{S}_i^b is a good proxy for the inverse of liquidity. This implies that $\partial S_i / \partial L_i \approx \beta_i S_i$. Thus, by subsuming ΔL_i in a parameter, we can write $(\partial S_i / \partial L_i) \Delta L_i \approx \beta_i S_i \Delta L_i = \lambda_{1i} \bar{S}_i^b$. According to Stoll (1978) and Saar (2000a, b), spreads are positively related to changes in volatility: $\partial S_i / \partial \Delta V_i > 0$. Using experimental evidence, Copeland and Friedman (1987) find that spreads also increase when dealers are exposed to price uncertainty ensuing from higher information heterogeneity among market participants: $\partial S_i / \partial H_i > 0$. Again for simplicity, we assume that the relationship between spread and volatility is roughly linear: $\partial S_i / \partial \Delta V_i \approx a_i + b_i \Delta V_i$, and define $\Delta(\Delta V_i) = c_i \Delta V_i$; this in turn implies that $(\partial S_i / \partial \Delta V_i) \Delta(\Delta V_i) = \lambda_{2i} \Delta V_i + \lambda_{3i} (\Delta V_i)^2$, where $\lambda_{2i} = a_i c_i$ and $\lambda_{3i} = b_i c_i$. Finally, we assume that $\partial S_i / \partial H_i = \lambda_{0i}$.

We also consider the possibility that shocks in the number of newly posted quotes, Δf_i ($\Delta f_i(j)$), or in their mean arrival rate, Δd_i ($\Delta d_i(j)$), affect ΔS_i ($\Delta S_i(j)$). Pasquariello (2005) shows that the impact of interventions on bid–ask spreads is greater when forex dealers hold less market power, because more of the profits and losses they experience from those trades have to be passed to investors. Saar (2000a) argues that when dealers compete for the incoming trade, spreads should decline. Hence, if we interpret f_i as measuring the intensity of competition in the currency market around interventions, then positive values for Δf_i should be accompanied by a decline in spreads. Grossman and Miller (1988) introduce a temporal dimension to the concept of liquidity by suggesting that immediate execution of a trade is valuable to investors. Their model derives the intuitive result that the greater the number of dealers providing immediacy, the greater the liquidity of a market. Cohen et al. (1981) relate the concept of liquidity to the degree of market thinness, defined as the inverse of the order arrival rate. Along these lines, negative (positive) shocks in the duration (Δd_i), as a proxy for more (less) intense trading activity during an intervention, should induce negative (positive) spread changes.

We evaluate the importance of these considerations by estimating two measurable extensions of Eq. (5) for ΔS_i and $\Delta S_i(j)$,

$$\Delta S_i = \lambda_{0i} + \lambda_{1i} \bar{S}_i^b + \lambda_{2i} \Delta V_i + \lambda_{3i} (\Delta V_i)^2 + \lambda_{4i} \Delta f_i + \lambda_{5i} \Delta d_i + \varepsilon_i \quad (6)$$

$$\Delta S_i(j) = \lambda_{0i} + \lambda_{1i} \bar{S}_i^b + \lambda_{2i} \Delta V_i(j) + \lambda_{3i} (\Delta V_i(j))^2 + \lambda_{4i} \Delta f_i(j) + \lambda_{5i} \Delta d_i(j) + \varepsilon_i(j), \quad (7)$$

for $j \in [-8, 8]$ and across all Central Bank trades i .⁴⁷ The following list provides a brief summary of the main hypotheses formulated for each of the coefficients in the above regressions:

λ_{0i} : A proxy for the change in bid–ask spreads due to shocks in the dispersion of beliefs among market participants. A positive (negative) estimate for λ_{0i} indicates that

⁴⁷ Because we want the regressors to measure shocks to information, liquidity, and volatility around SNB trades, we compute $\Delta V_i = \bar{V}_i - \bar{V}_i^b$ and $\Delta V_i(j) = V_i(j) - \bar{V}_i^b$, $\Delta f_i = \bar{f}_i - \bar{f}_i^b$ and $\Delta f_i(j) = f_i(j) - \bar{f}_i^b$, and $\Delta d_i = \bar{d}_i - \bar{d}_i^b$ and $\Delta d_i(j) = d_i(j) - \bar{d}_i^b$, where \bar{V}_i^b , \bar{f}_i^b , and \bar{d}_i^b are benchmarks constructed with the same procedure used for \bar{S}_i^b .

information heterogeneity is higher (lower) during interventions, i.e., that these trades induce destabilizing (stabilizing) information.

- λ_{1i} : A proxy for the effect of any shock in market liquidity due to interventions on the bid–ask spread (e.g., inventory shocks). Under the assumption that spreads are inversely related to liquidity, then if $\lambda_{1i} < 0$ interventions induce greater market liquidity and tighter spreads.
- λ_{2i} : A measure of the relation between changes in exchange rate volatility and the bid–ask spread. We expect this relation to be positive ($\lambda_{2i} > 0$).
- λ_{3i} : A measure of the degree of non-linearity in the above relation.
- λ_{4i} : A measure of the impact of shocks in the frequency of posted quotes during interventions on the bid–ask spread. If we interpret $\Delta f_i > 0$ as a proxy for greater competition in the forex market, then higher frequency should be accompanied by tighter spreads ($\lambda_{4i} < 0$).
- λ_{5i} : A measure of the relation between investors' need for immediacy (and dealers' ability to provide it) and the bid–ask spread. If we interpret Δd_i as a proxy for shocks to market thinness, then immediacy is valuable during interventions when $\lambda_{5i} > 0$.

4.2. Model estimation and results

We estimate Eqs. (6) and (7) via OLS for the subsamples of events i of type $h = I, I > 0$, $I < 0$, and $I \& C$. Tables 5a and 5b report the resulting cross-event parameters $\hat{\lambda}_{0i}$ to $\hat{\lambda}_{5i}$ when shocks in exchange rate volatility ΔV_i and $\Delta V_i(j)$ are measured by shocks in cumulative absolute returns $|r_i|$ and $|r_i(j)|$, respectively.⁴⁸ We establish their statistical significance using Newey–West standard errors, because of evidence of residual autocorrelation and heteroskedasticity.

Overall, this evidence suggests that changes in market liquidity and information shocks play a crucial role in explaining the increase in transaction costs around SNB interventions. The model performs satisfactorily: adjusted R^2 s range between 78% and 96% for ΔS_i in Eq. (6) and between 37% and 54% for $\Delta S_i(j)$ in Eq. (7).⁴⁹ The coefficient $\hat{\lambda}_{1i}$ is significantly negative in all cases (except when $I > 0$): SNB interventions (primarily USD sales) increase market liquidity, which translates into tighter spreads. The effect of volatility shocks on the absolute spread ($\hat{\lambda}_{2i}$) is positive and significant: Higher exchange rate volatility in proximity of SNB interventions (see Figs. 2b and c) induces dealers to widen their spreads.⁵⁰ For instance, a one standard deviation shock to daily aggregate absolute returns $|r_i|$ during SNB interventions ($\Delta V_i = 0.073$) translates into an increase in the bid–ask spread by $\Delta S_i = 0.36$ pips (since $\hat{\lambda}_{2i} = 4.949$ in Table 5a), i.e., into an increase

⁴⁸Both sign and significance of these parameters are not affected when ΔV_i and $\Delta V_i(j)$ are computed with shocks in daily square returns r_i^2 and $r_i^2(j)$, respectively.

⁴⁹Adjusted R^2 for Eq. (7) are lower because the cross-event series of spread changes $\Delta S_i(j)$ are noisier than the corresponding mean series ΔS_i . However, since some of the specifications for Eq. (6) are estimated over few events (18 for $h = I > 0$ and 16 for $h = I \& C$), the resulting inference may be problematic. Nonetheless, the coefficients $\hat{\lambda}_{0i}$ to $\hat{\lambda}_{5i}$ in Eq. (7), reported in Table 5b, are consistent in sign, magnitude, and significance with those in Eq. (6) from Table 5a. This confirms the robustness of our analysis to the selected degree of aggregation for shock variables in proximity of the event date τ_i .

⁵⁰Interestingly, $\hat{\lambda}_{2i}$ s are highest when excess volatility is lowest, when $I < 0$. This suggests that the impact of volatility shocks on spread changes is marginally decreasing. Such non-linearity is confirmed by negative and statistically significant $\hat{\lambda}_{3i}$ in most of the estimation subsamples.

Table 5a

Event shock decomposition: aggregate spreads \tilde{S}_i This table reports OLS estimates for the parameters λ_{0i} to λ_{5i} in the regression

$$\Delta S_i = \lambda_{0i} + \lambda_{1i}\tilde{S}_i^b + \lambda_{2i}\Delta V_i + \lambda_{3i}(\Delta V_i)^2 + \lambda_{4i}\Delta f_i + \lambda_{5i}\Delta d_i + \varepsilon_i, \quad (6)$$

where ΔS_i is the aggregate shock to the absolute spread computed over the entire interval surrounding the date τ_i when an event h occurs, $[\tau_i - 8, \tau_i + 8]$, for $h = I, I > 0, I < 0$, or $I \& C$, and where volatility shocks ΔV_i are measured by changes in $|r_i|$. Specifically, consider the i^{th} event of type h in the sample, occurring on day τ_i . Then, $\Delta S_i = \tilde{S}_i - \tilde{S}_i^b$, where \tilde{S}_i is the average absolute spread over the interval $[\tau_i - 8, \tau_i + 8]$ and \tilde{S}_i^b is a benchmark pre-intervention spread computed over the first 20 days preceding the third to last day before the event window $[\tau_i - 8, \tau_i + 8]$ that do not contain any past event of the same type. If we label such days with a “*” symbol, then $\tilde{S}_i^b = \sum_{j=-30}^{-11} S_i(j)/20$, where $S_i(j)$ is the absolute spread observed on day $\tau_i + j$. Consistently, we compute $\Delta V_i = \bar{V}_i - \bar{V}_i^b$, $\Delta f_i = \bar{f}_i - \bar{f}_i^b$, and $\Delta d_i = \bar{d}_i - \bar{d}_i^b$, where \bar{V}_i^b, \bar{f}_i^b , and \bar{d}_i^b are benchmarks for the average volatility (\bar{V}_i), frequency (\bar{f}_i), and duration (\bar{d}_i) over the interval $[\tau_i - 8, \tau_i + 8]$ constructed with the same procedure used for \tilde{S}_i^b . R_a^2 is the adjusted R^2 , DW is the Durbin–Watson statistic for residuals’ autocorrelation, and BP is the Breusch–Pagan chi-square statistic for residuals’ heteroskedasticity. Statistical significance is evaluated using Newey–West standard errors. A “*” denotes significance at the 10% level.

	$\hat{\lambda}_{0i}$	$\hat{\lambda}_{1i}$	$\hat{\lambda}_{2i}$	$\hat{\lambda}_{3i}$	$\hat{\lambda}_{4i}$	$\hat{\lambda}_{5i}$	R_a^2	DW	BP	N
<i>I</i>										
ΔS_i	8.600*	−0.901*	2.691*	−17.879*			31.51%	0.50	8.33*	86
ΔS_i	5.186*	−0.546*	4.949*	−9.456*	−0.0007	0.0035*	77.81%	0.75	1.75	86
<i>I > 0</i>										
ΔS_i	4.426	−0.411	2.198*	−14.459			−0.33%	0.76	5.78	18
ΔS_i	1.570	−0.164	1.145	−0.611	0.0007	0.0046*	88.00%	1.51	5.49	18
<i>I < 0</i>										
ΔS_i	14.930*	−1.596*	3.603*	−20.789			72.14%	0.99	1.77	68
ΔS_i	10.218*	−1.092*	5.198*	−10.881	−0.0005	0.0025*	84.35%	1.02	3.43	68
<i>I & C</i>										
ΔS_i	4.534	−0.455	22.485*	−123.61*			36.30%	0.84	5.90	16
ΔS_i	2.385*	−0.253*	16.428*	−42.358*	−0.0029*	0.0015*	96.33%	1.55	6.53	16

in annualized round-trip transaction costs by \$363 million. SNB activity has a further direct and destabilizing effect on the CHFUSD market resulting in greater transaction costs: after controlling for changes in liquidity and volatility, absolute spreads increase during SNB interventions—especially USD sales—($\hat{\lambda}_{0i} > 0$ in Tables 5a and b). These findings suggest that official SNB trades induce (at least temporary) misinformation and information heterogeneity among market participants.⁵¹

Sign and significance of $\hat{\lambda}_{0i}$ to $\hat{\lambda}_{3i}$ are unchanged, but their absolute magnitudes are generally reduced when accounting for shocks in the number of newly posted quotes (Δf_i and $\Delta f_i(j)$) and in the average time elapsing between them (Δd_i and $\Delta d_i(j)$). The coefficient

⁵¹Consistently, Dominguez (2006, p. 1053) observes that, in the short run, since “the information content of intervention signals may not be common knowledge, ... intervention operations themselves may initially add to the rational confusion in the market,” before eventually resolving market uncertainty.

Table 5b

Event shock decomposition: single spreads $S_i(j)$

This table reports OLS estimates for the parameters λ_{0i} to λ_{5i} in the regression

$$\Delta S_i(j) = \lambda_{0i} + \lambda_{1i}\bar{S}_i^b + \lambda_{2i}\Delta V_i(j) + \lambda_{3i}(\Delta V_i(j))^2 + \lambda_{4i}\Delta f_i(j) + \lambda_{5i}\Delta d_i(j) + e_i, \tag{7}$$

where $\Delta S_i(j)$ is the shock to the absolute spread over each day $\tau_i + j$ surrounding the date τ_i when an event h occurs, for $j \in [-8, 8]$ and $h = I, I > 0, I < 0$, or $I\&C$, and where volatility shocks $\Delta V_i(j)$ are measured by changes in $|r_i(j)|$. Specifically, consider the i^{th} event of type h in the sample, occurring on day τ_i . Then, $\Delta S_i(j) = S_i(j) - \bar{S}_i^b$, where $S_i(j)$ is the absolute spread observed in day $\tau_i + j$ and \bar{S}_i^b is a benchmark pre-intervention spread computed over the first 20 days preceding the third to last day before the event window $[\tau_i - 8, \tau_i + 8]$ that do not contain any past event of the same type. If we label such days with a “*” symbol, then $\bar{S}_i^b = \sum_{j=-30}^{-11} S_i(j)/20$. Consistently, for each measure of volatility ($V_i(j) = |r_i(j)|$), frequency ($f_i(j)$), and duration ($d_i(j)$) observed on day $\tau_i + j$, we compute $\Delta V_i(j) = V_i(j) - \bar{V}_i^b$, $\Delta f_i(j) = f_i(j) - \bar{f}_i^b$, and $\Delta d_i(j) = d_i(j) - \bar{d}_i^b$, where \bar{V}_i^b , \bar{f}_i^b , and \bar{d}_i^b are benchmarks for the average volatility (\bar{V}_i), frequency (\bar{f}_i), and duration (\bar{d}_i) over the interval $[\tau_i - 8, \tau_i + 8]$ constructed with the same procedure used for \bar{S}_i^b . R_a^2 is the adjusted R^2 , DW is the Durbin–Watson statistic for residuals’ autocorrelation, and BP is the Breusch–Pagan chi-square statistic for residuals’ heteroskedasticity. Statistical significance is evaluated using Newey–West standard errors. A “*” denotes significance at the 10% level.

	$\hat{\lambda}_{0i}$	$\hat{\lambda}_{1i}$	$\hat{\lambda}_{2i}$	$\hat{\lambda}_{3i}$	$\hat{\lambda}_{4i}$	$\hat{\lambda}_{5i}$	R_a^2	DW	BP	N
<i>I</i>										
$\Delta S_i(j)$	8.004*	−0.839*	−1.665*	5.218*			15.59%	0.91	81.78*	1,462
$\Delta S_i(j)$	5.640*	−0.577*	5.723*	−1.203	−0.0021*	0.0002	39.21%	1.24	228.9*	1,462
<i>I > 0</i>										
$\Delta S_i(j)$	3.105*	−0.279*	0.091	−0.378			0.82%	1.20	2.76	306
$\Delta S_i(j)$	1.342	−0.116	8.113*	−4.224*	−0.0035*	−0.0003*	37.08%	1.38	55.40*	306
<i>I < 0</i>										
$\Delta S_i(j)$	14.903*	−1.607*	−2.071*	19.576*			45.75%	1.07	63.75*	1,156
$\Delta S_i(j)$	11.426*	−1.222*	3.365*	12.699*	−0.0014*	0.0002	54.18%	1.16	169.1*	1,156
<i>I & C</i>										
$\Delta S_i(j)$	1.297	−0.073	−0.384	−1.768			−0.46%	1.05	2.43	272
$\Delta S_i(j)$	3.081*	−0.314*	15.586*	−11.692*	−0.0046*	−0.0002*	47.55%	1.37	45.37*	272

$\hat{\lambda}_{4i}$ for the former is mostly negative (and always significant in Eq. (6)), while estimates of λ_{5i} for the latter are mostly positive and significant. Evidence of $\hat{\lambda}_{4i} < 0$ implies that when (as in Figure 2g) dealers compete more intensely for incoming trades during SNB interventions (by posting more quotes), the bid–ask spread tightens. Evidence of $\hat{\lambda}_{5i} > 0$ instead indicates that, on average, immediacy is deemed more valuable in proximity of those transactions. For example, a one standard deviation decrease in the daily average delay between two newly posted quotes on the Reuters terminals around SNB interventions (118 seconds) translates into a decrease in the bid–ask spread by $\Delta S_i = 0.41$ pips (since $\hat{\lambda}_{5i} = 0.0035$ in Table 5a), i.e., into a decrease in annualized round-trip transaction costs by \$413 million. If we interpret d_i as a proxy for market thinness, then the

Table 6

Additional event shock decomposition

This table reports OLS estimates for the parameters λ_{0i} to λ_{5i} in the regression

$$\Delta S_i = \lambda_{0i} + \lambda_{1i} \bar{S}_i^b + \lambda_{2i} \Delta V_i + \lambda_{3i} (\Delta V_i)^2 + \lambda_{4i} \Delta f_i + \lambda_{5i} \Delta d_i + \varepsilon_i, \quad (6)$$

where ΔS_i is the aggregate shock to the absolute spread over the interval $[\tau_i - 8, \tau_i + 8]$ around the day τ_i when a trade of type h occurs (for $h = I, I_{\text{small}}, I_{\text{big}}, I_{\text{trend}},$ and I_{wind} defined in Section 3.3), and in the regression

$$\Delta S_i(j) = \lambda_{0i} + \lambda_{1i} \bar{S}_i^b + \lambda_{2i} \Delta V_i(j) + \lambda_{3i} (\Delta V_i(j))^2 + \lambda_{4i} \Delta f_i(j) + \lambda_{5i} \Delta d_i(j) + \varepsilon_i, \quad (7)$$

where $\Delta S_i(j)$ is a shock to the absolute spread over day $\tau_i + j$ in that interval. Volatility shocks ΔV_i and $\Delta V_i(j)$ are measured by shocks to $|r_i|$ and $|r_i(j)|$. The statistics are defined in the notes to Table 4a. Statistical significance is evaluated using Newey–West standard errors. A “*” denotes significance at the 10% level.

	$\hat{\lambda}_{0i}$	$\hat{\lambda}_{1i}$	$\hat{\lambda}_{2i}$	$\hat{\lambda}_{3i}$	$\hat{\lambda}_{4i}$	$\hat{\lambda}_{5i}$	R_a^2	DW	BP	N
<i>I</i>										
ΔS_i	5.186*	−0.546*	4.949*	−9.456*	−0.0007	0.0035*	77.81%	0.75	1.75	86
$\Delta S_i(j)$	5.640*	−0.577*	5.423*	−1.203	−0.0021*	0.0002	39.21%	1.24	228.9*	1,462
<i>I_{small}</i>										
ΔS_i	4.533*	−0.484*	6.838*	−6.974	−0.0011	0.0034*	78.24%	0.91	4.43	57
$\Delta S_i(j)$	4.571*	−0.471*	8.931*	−1.494	−0.0027*	0.0001	39.08%	1.25	126.7*	969
<i>I_{big}</i>										
ΔS_i	6.243*	−0.628*	4.460*	−12.053*	−0.0015*	0.0017*	83.19%	0.80	5.18	29
$\Delta S_i(j)$	6.501*	−0.658*	2.834*	−0.275	−0.0015*	0.0007	53.37%	1.25	313.6*	493
<i>I_{trend}</i>										
ΔS_i	6.274*	−0.649*	3.613	−6.085	−0.0005	0.0034*	77.15%	1.07	6.71	22
$\Delta S_i(j)$	6.062*	−0.622*	4.903*	2.812	−0.0018*	0.0003	37.04%	1.27	52.7*	374
<i>I_{wind}</i>										
ΔS_i	4.699*	−0.498*	6.399*	−15.080*	−0.0009	0.0034*	78.49%	0.87	3.54	64
$\Delta S_i(j)$	5.404*	−0.552*	6.511*	−2.823	−0.0023*	0.0002	40.35%	1.25	177.2*	1,088

dynamics of d_t in Fig. 2f suggest that SNB trades considerably affect investors’ ability to trade promptly, which reflects first in higher, then in lower transaction costs.

We also consider whether the relative importance of information, liquidity, and volatility considerations in explaining the observed shocks in transaction costs in proximity of SNB interventions plotted in Fig. 5 also depends on the direction and magnitude of these trades. For that purpose, we estimate Eqs. (6) and (7) across the additional intervention types defined in Section 3.3 ($h = I_{\text{small}}, I_{\text{big}}, I_{\text{trend}},$ and I_{wind}). The resulting coefficients $\hat{\lambda}_{0i}$ to $\hat{\lambda}_{5i}$, reported in Table 6, are again mostly consistent with the predictions listed in Section 4.1. Nonetheless, the extent by which SNB actions affect the degree of information heterogeneity and the relation between volatility, competition, market thinness, and spreads differs across event types. Big and trend-chasing interventions, which we find relatively ineffective in Section 3.3, lead to the most misinformation among market participants (i.e., the greatest $\hat{\lambda}_{0i}$). Yet, aggregate changes in absolute spreads in proximity of the latter interventions are instead independent of

excess volatility: $\hat{\lambda}_{2i}$ is not statistically significant for $h = I_{\text{trend}}$ in Table 6. Further, both SNB trades of type $h = I_{\text{big}}$ and I_{trend} have the largest positive impact on market liquidity ($\hat{\lambda}_{1i} < 0$), and are the least sensitive to competition and immediacy ($\hat{\lambda}_{4i}$ and $\hat{\lambda}_{5i}$ in Table 6), attenuating the increase in transaction costs displayed in Fig. 3c. This should not be surprising, since the CHFUSD market appears to anticipate the occurrence of those trades (Figs. 3a and b). More interestingly, when the SNB leans against the wind, the resulting degree of information heterogeneity $\hat{\lambda}_{0i}$ is as low as for $h = I_{\text{small}}$. This indicates that SNB interventions are the most effective (according to Fig. 3a) when investors and dealers agree upon an interpretation of their information content.

5. Conclusions

Are official interventions in the forex market a source of information or just noise? Is there any cost borne by investors stemming from Central Banks' attempts at managing currency fluctuations? And if so there is, why? Providing an answer to these questions by analyzing both the impact of Central Bank interventions on the process of price formation in the forex markets and the interaction among its many dimensions constitutes the contribution of this study to the exchange rate literature.

Our analysis shows that sterilized SNB interventions considerably affect different measures of exchange rate behavior, ex post volatility, market liquidity, and trading intensity both in the short and in the long run. Using an event study methodology (as well as alternative empirical strategies) on a joint dataset of indicative quotes and SNB transactions, we find that these signed trades, although representing only a small fraction of the average daily turnover in the CHFUSD market, have meaningful, asymmetric, and persistent effects on currency returns, especially when leaning against the wind, regardless of their size. Interestingly, the Swiss Franc market does not anticipate incoming interventions except when chasing the trend. Lastly, official USD purchases tend to follow a steady strengthening of the CHF, while official USD sales frequently come in reaction to a period of protracted CHF weakness, consistent with historical accounts of the monetary policy activity of the SNB (Rich, 1997; Peytrignet, 1999).

The SNB is much less successful in smoothing fluctuations of the currency or in reducing its variability, at least in the short run. Ex post measures of exchange rate volatility in fact always surge in proximity of interventions and stay high for many days afterward. This choice may, however, be optimal: for example, Rich (1997) argues that short-term currency volatility may allow the Swiss Central Bank to respond to unexpected shifts in preferences, hence to preserve price stability in the long run. Yet, despite their effectiveness, SNB interventions are also costly to investors: absolute and proportional spreads for the CHFUSD widen in a (statistically and economically) significant fashion around those trades, often prior to the actual intervention event. Because these effects are more pronounced in response to unanticipated SNB interventions, but are negligible in the control sample made of ex post uninformative customer transactions, we conclude that the potential information content of SNB interventions must play an important role in explaining their influence on the CHFUSD market. Consistently, the decomposition of spread shocks in proximity of SNB trades further reveals that a significant portion of the increase in transaction costs can be explained by greater information heterogeneity and fundamental volatility and lower market liquidity and competition among dealers. In

particular, large and trend-chasing interventions, the least successful in our sample, induce the greatest misinformation across market participants and reduce trading immediacy.

These findings have meaningful policy implications. Indeed, our analysis indicates that official interventions, even when effective against market momentum or disorderly market conditions, are often costly as well, not only for the Central Bank but also for investors and speculators. The evidence reported in this study suggests that this trade-off is complex, persistent, and non-trivial. It should therefore be at the center of any currency policy debate.

References

- Adams, D., Henderson, D., 1983. Definition and measurement of exchange market intervention. Staff Studies No. 126, Board of Governors of the Federal Reserve System.
- Amihud, Y., Mendelson, H., 1980. Dealership market: market-making with inventory. *Journal of Financial Economics* 8, 31–53.
- Andersen, T., Bollerslev, T., 1997. Heterogeneous information arrivals and return volatility dynamics: uncovering the long-run in high frequency returns. *Journal of Finance* 52, 975–1005.
- Andersen, T., Bollerslev, T., Diebold, F., Labys, P., 2001. The distribution of realized exchange rate volatility. *Journal of the American Statistical Association* 96, 42–55.
- Andersen, T., Bollerslev, T., Diebold, F., Labys, P., 2003. Modeling and forecasting realized volatility. *Econometrica* 71, 579–625.
- Bank for International Settlements, 1999. Triennial central bank survey of foreign exchange and derivatives market activity in 1998. Available at (<http://www.bis.org>).
- Bessembinder, H., 1994. Bid–ask spreads in the interbank foreign exchange markets. *Journal of Financial Economics* 35, 317–348.
- Bhattacharya, U., Weller, P., 1997. The advantage of hiding one's hand: speculation and central bank intervention in the foreign exchange market. *Journal of Monetary Economics* 39, 251–277.
- Bollerslev, T., Domowitz, I., 1993. Trading patterns and prices in the interbank foreign exchange market. *Journal of Finance* 48, 1421–1443.
- Bollerslev, T., Melvin, M., 1994. Bid–ask spreads and volatility in the foreign exchange market: an empirical analysis. *Journal of International Economics* 36, 355–372.
- Bossaerts, P., Hillion, P., 1991. Market microstructure effects of government intervention in the foreign exchange market. *Review of Financial Studies* 4, 513–541.
- Branson, W., 1983. Macroeconomic determinants of real exchange risk. In: Herring, R. (Ed.), *Managing Foreign Exchange Risk*. Cambridge University Press, Cambridge.
- Branson, W., 1984. A model of exchange rate determination with policy reaction: evidence from monthly data. In: Malgrange, P., Muet, P. (Eds.), *Contemporary Macroeconomic Modelling*. Basil Blackwell, Oxford, pp. 128–150.
- Chang, Y., Taylor, S., 1998. Intraday effects of foreign exchange intervention by the bank of Japan. *Journal of International Money and Finance* 17, 191–210.
- Chari, A., 2006. Heterogeneous market-making in foreign exchange markets: Evidence from individual bank responses to central bank interventions. *Journal of Money, Credit and Banking*, forthcoming.
- Chordia, T., Shivakumar, L., Subrahmanyam, A., 2004. Liquidity dynamics across small and large firms. *Economic Notes* 33, 111–143.
- Cohen, K., Maier, S., Schwartz, R., Whitcomb, D., 1981. Transaction costs, order placement strategy, and existence of the bid–ask spread. *Journal of Political Economy* 89, 287–305.
- Copeland, T., Friedman, D., 1987. The effect of sequential information arrival on asset prices: an experimental study. *Journal of Finance* 42, 763–797.
- Dacorogna, M., Müller, U., Nagler, R., Olsen, R., Pictet, O., 1993. A geographical model for the daily and weekly seasonal volatility in the foreign exchange market. *Journal of International Money and Finance* 12, 413–438.
- Dacorogna, M., Gençay, R., Müller, U., Olsen, R., Pictet, O., 2001. *An Introduction to High-frequency Finance*. Academic Press, New York.
- Dominguez, K., 1987. Exchange rate efficiency and the behavior of international asset markets. Unpublished Ph.D. Thesis, Yale University.

- Dominguez, K., 1998. Central bank intervention and exchange rate volatility. *Journal of International Money and Finance* 17, 161–190.
- Dominguez, K., 2003. The market microstructure of central bank intervention. *Journal of International Economics* 59, 25–45.
- Dominguez, K., 2006. When do central bank interventions influence intra-daily and longer-term exchange rate movements? *Journal of International Money and Finance* 25, 1051–1071.
- Dominguez, K., Frankel, J., 1993a. Does foreign exchange intervention matter? The portfolio effect. *American Economic Review* 83, 1356–1369.
- Dominguez, K., Frankel, J., 1993b. Does Foreign Exchange Intervention Work? Institute for International Economics, Washington.
- D'Souza, C., 2002. A market microstructure analysis of foreign exchange intervention in Canada. Bank of Canada Working Paper No. 2002-16.
- Edison, H., 1993. The effectiveness of central bank intervention: a survey of the literature after 1982. *Special Papers in International Finance*. Princeton University Press, Princeton.
- Evans, M., Lyons, R., 2002. Order flow and exchange rate dynamics. *Journal of Political Economy* 110, 170–180.
- Evans, M., Lyons, R., 2003. Are different-currency assets imperfect substitutes. In: De Grauwe, P. (Ed.), *Exchange Rate Economics: Where Do We Stand?* MIT Press, Cambridge (forthcoming).
- Fatum, R., Hutchison, M., 2003. Is sterilised foreign exchange intervention effective after all? An event study approach. *Economic Journal* 113, 390–411.
- Fedenia, M., Grammatikos, T., 1992. Option trading and the bid–ask spread of the underlying stocks. *Journal of Business* 65, 335–351.
- Fischer, A., 2003. The inaccuracy of Reuters reports for Swiss interventions. Swiss National Bank Working Paper No. 03.06.
- Fischer, A., 2004. Price clustering in the FX market: a disaggregate analysis using central bank interventions. Swiss National Bank Working Paper No. 04.04.
- Fischer, A., Zurlinden, M., 1999. Exchange rate effects of central bank interventions: an analysis of transaction prices. *Economic Journal* 109, 662–676.
- Goodhart, C., O'Hara, M., 1997. High frequency data in financial markets: issues and applications. *Journal of Empirical Finance* 4, 73–114.
- Goodhart, C., Ito, T., Payne, R., 1996. One day in June 1993: a study of the working of the Reuters 2000-2 electronic foreign exchange trading system. In: Frankel, J., Galli, G., Giovannini, A. (Eds.), *The Microstructure of Foreign Exchange Markets*. NBER Conference Report. The University of Chicago Press, Chicago, pp. 107–179.
- Grossman, S., Miller, M., 1988. Liquidity and market structure. *Journal of Finance* 43, 617–633.
- Guembel, A., Sussman, O., 2001. Optimal exchange rates: a market microstructure approach. Working paper. Said Business School, Oxford University.
- Hasbrouck, J., 1988. Trades quotes inventories and information. *Journal of Financial Economics* 22, 229–252.
- Hasbrouck, J., 1991. Measuring the information content of stock trades. *Journal of Finance* 46, 179–207.
- Hasbrouck, J., 1999. Security bid/ask dynamics with discreteness and clustering: simple strategies for modeling and estimation. *Journal of Financial Markets* 2, 1–28.
- Humpage, O., 1984. Dollar intervention and the deutschmark-dollar exchange rate: a daily time-series model. Federal Reserve Bank of Cleveland Working Paper No. 8404.
- Humpage, O., 1999. U.S. intervention: assessing the probability of success. *Journal of Money Credit and Banking* 31, 731–747.
- Humpage, O., Osterberg, W., 1992. Intervention and the foreign exchange risk premium: an empirical investigation of daily effects. *Global Finance Journal* 3, 23–50.
- Kaminsky, G., Lewis, K., 1996. Does foreign exchange intervention signal future monetary policy? *Journal of Monetary Economics* 37, 285–312.
- Kearns, J., Rigobon, R., 2005. Identifying the efficacy of central bank interventions: evidence from Australia and Japan. *Journal of International Economics* 66, 31–48.
- Lewis, K., 1995. Occasional intervention to target rates. *American Economic Review* 85, 691–715.
- Lyons, R., 2001. *The Microstructure Approach to Exchange Rates*. MIT Press, Cambridge.
- Müller, U., Dacorogna, M., Olsen, R., Pictet, O., Schwarz, M., Morgenegg, C., 1990. Statistical study of foreign exchange rates, empirical evidence of a price change scaling law, and intraday analysis. *Journal of Banking and Finance* 14, 1189–1208.
- Mussa, M., 1981. The Role of Official Intervention. Group of Thirty Occasional Paper No. 6.

- Naranjo, A., Nimalendran, M., 2000. Government intervention and adverse selection costs in foreign exchange markets. *Review of Financial Studies* 13, 453–477.
- Neely, C., 2000. The practice of central bank intervention: looking under the hood. *Central Banking* 11, 24–37.
- Neely, C., 2005. An analysis of recent studies of the effect of foreign exchange intervention. Federal Reserve Bank of St. Louis Working Paper No. 2005-030A.
- O'Hara, M., 1995. *Market Microstructure Theory*. Blackwell Publishers, Cambridge.
- Osterberg, W., Wetmore Humes, R., 1993. The inaccuracy of newspaper reports of U.S. foreign exchange intervention. *Economic Review*, Federal Reserve Bank of Cleveland 29, 25–33.
- Osterberg, W., Wetmore Humes, R., 1995. More on the differences between reported and actual U.S. central bank foreign exchange rate intervention. Federal Reserve Bank of Cleveland Working Paper No. 9501.
- Pasquariello, P., 2003. Market frictions in domestic and international financial markets: chapter 3. Unpublished Ph.D. Thesis, Stern School of Business, New York University.
- Pasquariello, P., 2005. Central bank intervention and the intraday process of price formation in the currency markets. Working paper, Ross School of Business, University of Michigan.
- Payne, R., Vitale, P., 2003. A transaction level study of the effects of central bank intervention on exchange rates. *Journal of International Economics* 61, 331–352.
- Peiers, B., 1997. Informed traders intervention, and price leadership: a deeper view of the microstructure of the foreign exchange market. *Journal of Finance* 52, 1589–1614.
- Peytrignet, M., 1999. Swiss monetary policy under a flexible exchange rate regime: monetary targets in practice. Working paper, Bank of Canada.
- Rich, G., 1997. Monetary targets as a policy rule: lessons from the Swiss experience. *Journal of Monetary Economics* 39, 113–141.
- Saar, G., 2000a. Demand uncertainty and the information content of the order flow. Working paper, Stern School of Business, New York University.
- Saar, G., 2000b. Prices and spreads in sequential markets with information imperfections. Working paper, Stern School of Business, New York University.
- Sarno, L., Taylor, M., 2001. Official intervention in the foreign exchange market: is it effective and, if so, how does it work. *Journal of Economic Literature* 39, 839–868.
- Stein, J., 1987. Informational externalities and welfare-reducing speculation. *Journal of Political Economy* 95, 1123–1145.
- Stoll, H., 1978. The supply of dealer services in securities markets. *Journal of Finance* 33, 1133–1151.
- Taylor, D., 1982. Official intervention in the foreign exchange market, or, bet against the central bank. *Journal of Political Economy* 90, 356–368.
- Vitale, P., 1999. Sterilised foreign exchange intervention in the foreign exchange market. *Journal of International Economics* 49, 245–267.
- Vitale, P., 2003. Foreign exchange intervention: how to signal policy objectives and stabilise the economy. *Journal of Monetary Economics* 50, 841–887.