Information Content and Predictability of Extreme Prices in Financial Markets*

Angelo Ranaldo†
Swiss National Bank

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†Angelo Ranaldo, Swiss National Bank, Research, Börsenstrasse 15, P.O. Box 2800, Zurich, Switzerland. E-mail: angelo.ranaldo@snb.ch, Phone: ++41.44.6313826, Fax: ++41.44.6313901.

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Abstract: Extreme prices are still unchartered territory. By defining extremes as maximum and minimum prices during a pre-specified time interval, this research sheds new light on when, how and why high and low prices occur. We investigate a representative asset for currency, stock and bond markets across different time granularities (hours, days and months). Some relevant stylised facts emerge. First, the occurrence of extreme price clusters at the beginning and end of the month. Their intraday timing, however, is less regular and more dependent on microstructure and behavioural issues. Second, extreme prices are sticky. Highs, lows and range are thus significantly auto-correlated and cross-correlated. Third, high and low prices are cointegrated. We find that pre-scheduled announcements of major macroeconomic news bulletins are a significant primitive source for extreme price occurrences. Using a vector autoregressive model with error correction, we provide evidence on the predictability of extreme prices.

Keywords: high and low prices; extreme prices; range; autocorrelated returns; VAR; cointegration; predictability; resistance levels; technical analysis; news impact.

JEL Classifications: G10; G12; G13; G14; C32; C53.

1 Introduction

What is the information content of extreme prices in financial markets? Are high and low prices over a pre-defined time interval characterised by any stylised facts? And if so, are these stylised facts consistent with the random walk hypothesis or efficient market's idea? Do these stylised facts hold across asset classes and time horizons? Are extremes originated by the release of public information? Can we identify which news bulletins convey extremes? Can we predict extreme prices? This research attempts to provide answers to these essential questions that have so far drawn little attention in the literature.

The informativeness of high and low prices resides in four main domains: First, the human being's mind. Kahneman and Tversky (1979) show that when forming estimates, people start with some initial arbitrary value, and then adjust it in a slow process. In more general terms, behavioural finance shows that agents' behaviours generally depend on reference levels. In these and other forms of mental accounting and framing, past high and low prices typically represent the reference values for future resistance levels (Curcio and Goodhart (1992), DeGrauwe and Decupere (1992) and Osler (2000)). Second, as highlighted in market microstructure, high and low prices convey information about liquidity provision and the price discovery process. For instance, Menkhoff (1998) shows that high and low prices are very informative when it comes to analysing the order flow in foreign exchange markets. Third, high and low prices actually shape the decisions of many kinds of market participants. Technical analysts' decisions hinges on past high and low prices. Recently, academics have been taking more interest in technical analysis. They have documented that technical analysis' strategies may succeed in extracting valuable information from typical chartist indicators, such as candlesticks and bar charts based on past high, low, and close prices (e.g. Lo, Mamaysky, and Wang (2000)). But there are many other market participants who consider past extreme prices highly important. For instance, limit prices in stop-loss orders placed by proprietary traders and discretionary managers often match the farthest prices in a bygone representative period. It can be either due to a management decision (take-profit or stop-loss strategies) and/or self-imposed discipline. More generally, any investor using some path-dependent strategy typically tracks the past history of extreme prices. Finally, extreme prices are highly informative as a measure of dispersion. The linear difference between high and low prices is known as the range. Since Feller (1951), there has been a long tradition on the range[1]. This literature shows that the

[1] Among others, Parkinson (1980), Garman and Klass (1980), Beckers (1983), Ball and Torous (1984), Rogers and Satchel (1991), Kunitomo (1992) and more recently Andersen and

range-based estimation of volatility is highly statistically efficient and robust to many microstructure frictions.

This research has three main objectives: First, to perform an explorative analysis into the information content of extreme prices. In this explorative analysis, we examine the main statistical characteristics of high and low prices across different time granularities (specifically: hourly, daily and monthly) and different asset classes. We analyse more than a decade's worth of data in a high-frequency database containing futures contracts on the S&P index and on the 10-year US treasury bonds as representative assets for the stock and bond markets, and the Swiss franc-US dollar spot exchange rates for the currency market. This large trade-by-trade database enables us to analyse extreme price behaviours over representative periods of recession and expansion, and to infer stylised facts holding for different categories of financial assets.

The second objective is to investigate one of the possible sources of extreme prices, i.e. public information announcements. First, we analyse whether and to what extent the occurrence of extremes is more likely after the announcement of major pre-scheduled US macroeconomic news bulletins. Second, we examine how the surprise or unexpected component in the news announcement characterises the extreme price behaviour.

Finally, we propose an econometric specification for modelling high and low prices. Consistent with the findings in the first part of the paper, we present a simple implementation of a vector autoregressive model with error correction ("VECM") between high and low prices. We examine the predictive ability of this model to forecast future high and low prices.

Our results shed light on the following stylised facts. First, extreme price are sticky. Thus, the price change from the previous to the current high price ("high-to-high price change") follows an autocorrelated pattern. Inertia in extreme prices holds for shorter and longer time horizons. In contrast with the standard Brownian motion setting, stickiness in extreme prices holds even if we consider the price change from the first to the highest trading price of a given time interval ("first-to-high price change"). Our findings show that the same patterns hold for low-to-low and first-to-low price changes. Second, when we consider a longer time interval, the high and low prices tend to cluster at the very beginning and end of the time interval. This means that it is more likely for extreme market prices to be observed at the beginning or the end of a given month. By contrast, the intraday location of highs and lows is much more irregular and dependent on behavioural and microstructure aspects. Finally, the joint behaviour of high

Bollerslev (1998), Yang and Zhang (2000), Alizadeh, Brandt, Diebold (2002) and Brandt and Diebold (2003), Christensen and Podolski (2005) and Martens and van Dijk (2005).

and low prices is considered. Two main stylised facts emerge. First, the range is also serially autocorrelated. Second, high and low prices deviate in the short run but steadily converge in the long run. In other words, high and low prices have a cointegrated pattern.

Second, we investigate one possible reason behind the occurrence of extreme prices: public information releases. We find that extremes in the bond, currency and equity markets are significantly associated with US macroeconomic news. For some macroeconomic bulletins, news announcements cause more than 50% of the daily extremes. Not only the time, but also the content of the news announcement characterises the formation of extreme prices. A positive news surprise generally impacts positively on the US dollar and negatively on equity and bond futures. However, the specific analysis of the bond futures reaction to news announcements conditional on business cycles suggests that news impacts differently across economic regimes. In particular, good news is bad news for bond investors only in cases of expansion.

Third, we provide evidence of the predictability of extreme prices. Vector autoregressive modelling with error correction is the natural econometric system for modelling all the stylised facts mentioned above. We show that – although it is simple – this econometric specification represents a straightforward and efficient method to capture the information content of high and low prices. The predictability of extreme prices appears to be at odds with the difficulty of forecasting asset returns. A long tradition of empirical work (e.g. Fama (1970 and 1991)) supporting the efficient market hypothesis provides evidence that asset prices in a fixed point in time (say, at closing) are hardly predictable. This paper shows that unpredictability does not hold for extreme prices and that the next extreme prices can be forecast by simply using past high and low prices that are readily available.

The present paper is structured as follows. Section 1 introduces some analytical aspects of the stochastic behaviour of high and low prices. Section 2 shows the main empirical findings of the explorative analysis. Section 3 analyses whether extremes are associated with macroeconomic news. Section 4 presents the main results arising from the VECM model, while Section 5 presents the forecasts based on the VECM model. Section 6 concludes the paper.

2 Some analytical aspects on high and low prices

In this first part of the paper, we survey some simple analytical aspects of the stochastic behaviour of high and low prices. Using the standard properties of a geometric Brownian motion, we form a number of hypotheses on the stochastic process of high and low prices. These hypotheses will be tested in the subsequent parts of this research.

We first focus on the position in time of the high and low prices. Feller (1968) shows that one of the surprising features of the chance fluctuations in coin tossing finds its expression in the arc-sine law. To illustrate this issue, Feller considers a path of n tosses of a coin. Assigning +1 (-1) for heads (tails), the s_k equals the excess of the accumulated number of heads over tails at the kth trial. The arc-sine law implies that the maximum (and minimum) of s_k is more likely to occur when $k = 0$ or $k = n$, in other words at the very beginning and end of the game. It turns out that the arc-sine law applies for much more general stochastic processes, in particular for Brownian motions (see, e.g., Revuz and Yor (1999)).

Let us assume that the asset price S follows a standard one-dimensional Brownian motion. We decompose the life-time of the asset into k periods from $k = 1, \ldots, K$ that are distributed homogenously and equally over time. These k periods are, in turn, decomposed in further into $t = 1, \ldots, T$ homogenous sub-periods. Let $S_{k,t}$ be the asset price at time t of period K. Without loss of generality, let us assume that the starting value of $S_{k,t}$ is $S_{1,1} = 0$. The highest level of the asset price can be reached at any time t within period $k = 1$. We define this first high price as $p^H_{k=1,t} = \max\limits_{1 \leq t \leq T} S_{k=1,t}$. The arc-sine law tells us that if the fraction of the trading period is $x = 1/k$, then the arc-sine cumulated distribution for the occurrence of $p^H_{k=1,t}$ is $A(x) = \left(\frac{2}{\pi}\right) \arcsin \sqrt{x}$. Plotting a graph for the marginal probability of $p^H_{k,t}$ across the time of the trading period, we would observe a well-defined and symmetrical U-shape. This argument brings us to the first hypothesis to test:

Hypothesis 1: High and low prices within a given time interval are more likely to occur at the beginning and end of that time interval.

Let us assume that we have observed the highest price occurred in the first period or trading session, $p^H_{k=1,t}$. Now we are interested in the highest level reached by the asset price in the second period starting from $p^H_{k=1,t}$, i.e. from the highest value of the first period. We call this second high price $p^H_{k=2,t} = \max\limits_{1 \leq t \leq T} S_{k=2,t}$. To see more clearly the dependence of $p^H_{k=2,t}$ in relation to its predecessor, $p^H_{k=2,t}$ can be simply restated as follows:

$$p^H_{2,t} = \max\left(S_{2,t} - S_{1,t}\right) + \max\left(S_{1,t}\right) = \max\left(S_{2,t} - p^H_{1,t}\right) + p^H_{1,t} \qquad (1)$$

Here it is evident that the value and the occurrence time of $p^H_{k,t}$ depends on

$p^H_{k-1,t}$. This definition of high-to-high price change implies overlapping increments of the Brownian motion process. We would then expect the high-to-high price changes to be autocorrelated. More specifically, we test the following hypothesis:

Hypothesis 2: Price changes between successive high (low) prices are serially correlated.

In a Brownian motion setting, this dependence disappears if we consider the highest asset price within period k starting from the first value of period k. Now $p^H_{k,t}$ becomes

$$p^H_{k,t} = \max\left(S_{k,t}\right) = \max\left(S_{k,t} - S_{k,1}\right) + S_{k,1} \tag{2}$$

That is, $p^H_{k,t}$ is independent of S_{k-1}. The Williams theorem suggests another method to represent the stochastic behaviour of maxima and minima and their independence. According to this theorem, a Brownian path can be decomposed into three independent components, namely a standard Brownian motion and two Bessel processes. The first element lasts until a positive pre-established level is reached, say α. The second element is a Bessel process that starts from the occurrence of α and lasts until the process no longer has any negative values. The last element is a Bessel function enduring until the maximum is reached, say b. The three consecutive elements form a Brownian motion killed when it first hits b (see Revuz and Yor (1999)). There is thus a further hypothesis to test:

Hypothesis 3: Price changes from the first to the highest price of a given interval are independent and should not follow an autocorrelated pattern.

The same reasoning can be applied to the range. Let us define the range in period k as $R_{k,t} = \max\left(S_k\right) - \min\left(S_k\right)$. As before, we can reformulate $R_{k,t}$ as follows:

$$R_{k,t} = \max\left(S_{k,t} - S_{k,1}\right) + S_{k,1} - \min\left(S_{k,t} - S_{k,1}\right) - S_{k,1} \tag{3}$$

where the two terms $S_{k,1}$ cancel each other out and R_k proves to be independent of the information set $\Im_{k-1}$.

Hypothesis 4: The range, as the difference between the highest and lowest prices within a given interval, is independent across time and should not be serially correlated.

Another way to understand why first-to-high, first-to-low and the range should be independent identically-distributed random variables is to evoke the Levy theorem of Brownian local time. To obtain an intuitive view of the relation between Brownian motion and distribution of maxima (or minima), consider a *reflecting* Brownian motion $W^{+} = \{|W_t| : t \geq 0\}$. It can be shown that this is a linear diffusion. Let us suppose that $\breve{M}_t = \sup\{W_s : s \leq t\}$ and $W^0 = \sup\left\{\breve{M}_t - W_t : t \geq 0\right\}$. According to Lévy, it can be shown that W^0 is identical in law to W^{+}. See Itô and McKean (1974) for a formal proof. We can go a step further and obtain the distributional properties relating to the reflecting Brownian motion and the maxima. Let $t \longrightarrow \ell(t, 0)$ denote the local time at zero mentioned above. Lévy shows that the local time for an arbitrary point x can be represented by

$$\ell(t, x) = \lim_{\epsilon \longrightarrow 0} \frac{1}{2\epsilon} \int_0^t \imath_{(x-\epsilon, x+\epsilon)}(W_s)\, ds \tag{4}$$

where $\imath_{(.)}$ is the indicator function. This gives the occupation time formula:

$$\int_0^t \imath_A(W_s)\, ds = \int_A \ell(t, x)\, dx \tag{5}$$

where A is a bounded Borel-measurable function in $\mathbb{R}$. The relation between W^{+} and W^0 found above can be extended to the relation between these two joint distributions:

$$\{|W_t|, \ell(t, 0) : t \geq 0\} \sim \left\{\left(\breve{M}_t - W_t, \breve{M}_t\right) : t \geq 0\right\} \tag{6}$$

The final hypothesis we shall test concerns the joint behaviour of high and low prices across time. This hypothesis states that the high and low prices have an embedded convergent path in the long run.

Hypothesis 5: The high and low prices are cointegrated.

Even if the cointegrated scheme should appear intuitive, we can apply the microstructure theory to support this hypothesis. A typical price formation model in a market microstructure assumes that an asset value has a double identity: the true asset value and the market price. The former is the fundamental and unobservable value of an asset. The latter is the visible market face of the true value. The market price can temporarily deviate from the true value but its behaviour has to be connected to the true value. The same reasoning holds for high and low prices that may be regarded as deviations from the true asset value of a given asset. This deviation can be a transient departure due to information motives, liquidity factors or microstructure effects (e.g. bid-ask spread bounces, price discreteness, trading pressure, and so on). The re-convergence of high and low transaction prices to the true asset value implies that high and low prices can deviate in the short but not the long run. In statistical terms, we can state that (high and low) asset prices are not typically covariance stationary but the high-low linear difference, i.e. the range, should be stationary. Thus, the time series of high and low prices in levels should be *I(1)* but their difference should be *I(0)*. This implies cointegration between highs and lows.

3 Some empirical evidence on extreme prices

3.1 Data

Throughout this paper, we will refer to the following definitions: the high-to-high price change is the logarithmic difference between the highest price level that occurred in the current and previous periods (shown as "HH" in the tables). The first-to-high price change is the logarithmic difference between the highest and first prices of a given time interval ("FH" in the tables). When we consider the daily time interval, the first price refers to the opening price of the daily trading session of the Chicago Mercantile Exchange (CME) and Chicago Board of Trade (CBOT), and the first quoted spot exchange rate for CHF/USD. When we consider intraday and monthly timeframes, "first price" denotes the first traded price of the corresponding time intervals. The same definitions apply for low prices, namely low-to-low ("LL") and first-to-low ("FL"). The range is the logarithmic difference between high and low prices. Finally, the last-to-last price change is the logarithmic difference between the last price level that occurred in the current and previous periods ("CC" in the tables). In the daily timeframe, this corresponds to the (log) return between successive closing prices.

The database has kindly been provided by Swiss-Systematic Asset Management SA, Zurich. Since it includes only the open-outcry data for the S&P futures, we supplemented this dataset with the S&P futures Globex data. The sample periods are from the beginning of January 1993 to the end of December 2003 for the CHF/USD exchange rate, and from 7 November 1988 to the end of May 2003 for futures on the S&P 500 Index and treasury notes. This specific starting date for the futures sample corresponds to the introduction of extended trading hours at the CBOT. From that date, the trading day on the CBOT was from 8:20 a.m. to 3 p.m. Eastern Time (henceforth ET). All time indications used in this paper are in ET. The trading hours at the CBOT imply that we cannot analyse the news impact for Consumer Credit bulletins that occurs at 3 p.m. The CME Globex data are from 9 September 1993 (inception of the Globex system) to May 2003. The CME trading hours went from 9:30 a.m. to 4:15 p.m. for the open-outcry trading in designated pits and from 6 p.m. to 9:15 a.m. at the Globex trading platform. This prevents us from analysing the news impact for Capacity Utilization and Industrial Production bulletins that occur at 9:15 a.m. The data contain the time stamp to the nearest minute and transaction prices of all trades for the futures contracts. We use the most actively traded nearest-to-maturity or cheapest-to-delivery futures contract, switching to the next-maturity contract five days before expiration, cf. Andersen et al. (2004). For the currency data, we use the FXFX Reuters midquote price (the average price between the representative ask and bid quotes). Although indicative quotes have their shortcomings, the comparison between the electronic foreign exchange trading system Reuters 2000-2 and FXFX Reuters shows that "FXFX indicative quotes can be taken as a very good and close proxy for that in the Reuters 2000-2" (Goodhart, Ito and Payne (1996), page 126).

Table 1 reports the number of observations for each asset. It also shows some descriptive statistics from different definitions of price change. We note that the descriptive statistics of the high-to-high (HH), first-to-high (FH), low-to-low (LL) and first-to-low price changes (FL) are similar to those of the last-to-last price changes (CC). Returns on S&P index futures (treasury yield futures) have the highest (lowest) standard deviations. As expected, skewness and excess kurtosis of any price change definition decrease with the length of the time interval. This also means that the longer the time interval of returns, the closer their distribution to a Gaussian distribution. Among these assets, price changes on treasury yield futures are characterised by the most negatively skewed values and the highest kurtosis. By construction, first-to-high (first-to-low) price changes are positively (negatively) skewed. In fact, first-to-high (first-to-low) price change must be a non-negative (non-positive) value asymmetrically ranging from zero (minus infinite) to infinite (zero). However, first-to-high (first-to-low) price changes are more positively (negatively) skewed than high-to-high (low-to-low) price changes.

3.2 Location of high and low prices

Figure 1 and 2 shows when high and low prices typically occur within the trading day and month. These patterns seem to weakly support hypothesis 1, which states that high and low prices should cluster at the very beginning and end of the time intervals. For the intraday patterns, only the S&P futures show a well-defined U-shaped pattern. However, Figure 1B shows that extreme S&P futures prices during the open-outcry trading hours occur much more frequently around the beginning and end of the trading day than we would have expected from the arc-sine law (see grey lines). By extending the trading time by one hour (from 8:15 to 9:15 a.m.) from the CME Globex, we can observe how equity futures extremes are located around news announcements at 8:30 a.m. Figure

2 shows that the introduction of the Globex system only partially changed this pattern. Hence, whether this intraday U-shape comes from the existence of non-trading overnight time remains an open question. As we know from the previous literature on intraday market behaviours – e.g. Brock and Kleidon (1992), Chung, Van Ness and Van Ness (1999), Lehmann and Modest (1994) and Olsen et al. (1997) – volatility, trading volume and bid-ask spread also follow an intraday U-shape behaviour and this is essentially due to the overnight non-trading time. Figure 1A on the intraday location of highs and lows on the foreign exchange market clearly shows that the occurrence of extremes depends on many other aspects. In particular, it seems that the trading hours in the world's three major regions determines the location of extremes, namely those of the Asian markets (Tokyo opens at 7 p.m. and closes at 4 a.m.), the European markets (London opens at 3 a.m. and closes at 12 p.m.) and the US markets (NY opens at 8 a.m. and closes at 5 p.m.).[2] It can be seen that the probability peaks for extreme prices correspond to the open and close time of the major markets. Acar and Toffel (1999) analysed futures trading in three major currencies at the CME and found that the timing of highs and lows deviated widely from that implied by the random walk hypothesis. They argue that this departure may be due to the pervasive influence of positive drifts in currency markets, stochastic volatility and leptokurtosis.

The intraday pattern of the treasury yield futures at the CBOT also deserves close consideration. We note that the probability of highs and lows increases at 8:30[3] and 10[4] a.m., when the major macroeconomic news bulletins are released. Related to this finding, Bollerslev, Cai and Song (2000) found two spikes in intraday volatility at 8:30 and 10 a.m. on the US treasury bond market. As documented in the literature (e.g. Andersen et al. (2004) and Christiansen and Ranaldo (2005)), U.S. bonds tend to react more than US stocks to macroeconomic news. Thus, these results suggest that the location of extreme prices critically depends on behavioural and microstructure aspects such as the timing and characteristics of a trading session, trading activity across different time zones and scheduled announcements of major news bulletins.

The location of intra-monthly extreme prices fits more with the arc-sine law. Figure 5 shows that the occurrence of high and low prices is more probable at

[2]The literature includes many other papers showing how trading activity across different geographic regions determine intraday seasonalities on forex markets; see e.g. the recent contribution of Ito and Hashimoto (2005).

[3]See: GDP, Nonfarm Payroll Employment, Retail Sales, Personal Income, Personal Consumption Expenditures, Business Inventories, Trade Balance, Producer and Consumer Price Indices, Housing Starts, Index of Leading Indicators and Initial Unemployment Claims.

[4]See: New Home Sales, Factory Orders, Construction Spending, Consumer Confidence Index, and NAPM Index.

the beginning or at the end of the month. This may suggest that when larger time windows are used, the price behaviour is more comparable to a geometric Brownian motion.

3.3 Autocorrelation

The second hypothesis defined above is that high-to-high (low-to-low) price changes are time-dependent and therefore we expect to observe some autocorrelation. In contrast, hypothesis 3 suggests that first-to-high (first-to-low) price changes should be independently distributed across time and thereby no autocorrelation is expected. Table 2 shows that *both* high-to-high and first-to-high price change definitions follow a significantly autocorrelated process.[5] This persistent pattern lasts for several lags. Since the autocorrelation coefficients die off geometrically with increasing lags, the price change series involving extreme prices seem to obey a low-order autoregressive process. In general, the number of significant lags decreases with the length of the time interval. Thus, autocorrelation patterns are highly significant over intraday and daily periods and tend to disappear on a monthly basis. It is also worth noting that the bid-ask bounce apparently does not affect any definition of price changes even on an hour-by-hour basis. In fact, only in a few cases does the first lag of the autocorrelation function have a significantly negative coefficient.

The S&P and treasury yield futures appear to be those most affected by time dependence. By contrast, the Swiss franc-US dollar spot exchange rate has no autocorrelated patterns over a monthly timeframe. Contrary to a priori expectations based on the Brownian motion characteristics, the autocorrelation of first-to-high and first-to-low returns on these futures assets exist and are very significant.

We have analysed whether any periodic fluctuations or time seasonality affect our results. To do this, we have used different methods and have detected seasonalities only for intraday price changes. Three main methods were used: first, filtering out seasonalities with averages for the same time of day/week/month; second, regressing seasonal dummy variables on the various definitions of price change and then using the regression residuals as deseasonalized time series; and third, using the flexible Fourier form after Andersen and Bollerslev (1997 and 1998). Our results (not tabulated)[6] suggest that the documented autocorrelated pattern in high-to-high, first-to-high, low-to-low, first-to-low and range

[5] For the sake of presentation, low-to-low and first-to-low price changes are not shown in Table 2. However, all findings relating to high prices also hold for low prices. These results are available upon request.

[6] This additional analysis is available upon request.

still remains after adjusting for intraday seasonalities, and in some instances autocorrelation is even more noticeable.

According to hypothesis 4, the range should be independent across time. For the high and low price changes, we find that the range is significantly autocorrelated especially over intraday and daily time intervals. The serial autocorrelation pattern of the range is basically identical to that of the first-to-high and first-to-low price changes. This autoregressive pattern recalls the broad idea of volatility clustering (Mandelbrot (1963)) and the autoregressive conditional heteroskedastic models (e.g. Engle (1982)). In the same line of reasoning, the autoregressive process in the range can be explained by a non constant variance over time that is conditional on the past.

The Granger-causality tests in table 3 show that past high (low) prices are related to current low (high) prices. Cross-correlations are strong for all kinds of intraday relations. On a daily basis, open-to-close returns appear to Grange-cause open-to-high and open-to-low price changes, and open-to-high and open-to-low returns cause each other. The fact that open-to-close returns Grange-cause open-to-high and open-to-low price changes can be due to the longer length of the open-to-close period. Put differently, the open-to-close period embraces wider information set than open-to-high and open-to-low intervals. However, in many instances, past open-to-high and open-to-low returns have a significant bearing on current open-to-close return even over daily and monthly time intervals. It is also noticeable that the effect of past open-to-low returns on open-to-high returns seems to be stronger. This may suggest that price level adjustments coming from below have a greater effect.

The stickiness of high and low price may be due to the existence of resistance levels and the use of rounded and reference numbers. The nature of rounded or reference numbers may be varied: e.g. mental accounting, price discreteness, reference prices in related markets such as strike prices in derivative instruments. The inertia of extreme prices may also be due to standard procedures for forming expectations that rely on past values. Expectations of future high and low prices are typically based on the recent high and low prices. Thus, past market turning points tend to determine the next trading range. High and low prices therefore represent the oncoming support and resistance levels. Finally, these kinds of persistence may be due to the ways in which information is released and in which agents process information into prices. Hung and Plott (2001) show how information cascades can engender “herding” behaviours and thus a prolonged process of price adjustments. Furthermore, analysis of certain information items may objectively be time-consuming and undergo a lengthy process before being completely incorporated into asset prices.

3.4 Cointegration

Hypothesis 5 states that high and low prices have a cointegrated behaviour. Since non-stationarity is a pre-condition of cointegration, high and low prices were tested for unit roots using the augmented Dickey-Fuller (ADF) and Phillips Perron tests. All the time series over all the timeframes appear to be *I(1)* in levels and *I(0)* in differences. According to these tests, stationarity is strongly rejected. The results of the unit root tests are available from the author upon request.

Table 4 shows the Johansen tests for cointegration. For all the three assets and timeframes considered in this research, high and low prices appear to be strongly cointegrated. Likelihood ratio tests allow rejection of the null hypothesis of no cointegration at 1% in all cases but one (for CHF/USD monthly data the rejection is at 5% of significance level). Fiess and MacDonald (1999, 2002) show daily cointegration between high, low, and close for three exchange rates: USD/DEM, USD/JPY and GBP/USD. Our results suggest that cointegration exists for shorter and longer time granularities, longer sample periods and for other asset classes.

4 Macroeconomic new announcements

There are many possible reasons behind the occurrence of extreme prices. Here we limit our analysis to only one possible driver: macroeconomic new announcements. In particular, we analyse (1) whether the occurrence of the high and low price of the day is related to the announcements of major US macroeconomic news, and (2) whether the surprise or unexpected component of the news announcement impacts on extreme prices. The former question focuses on the time of the news announcement (hereafter we will refer to "announcement effect"). The latter issue refers to its information content ("news effect").

We obtain the announcement data from Informa Global Markets (Europe) Ltd.[7] For each different macroeconomic announcement, we obtain a time series of the realised values as well as market forecasts based on survey expectations. For most news items, the news data are available during the sample period for

[7] In previous studies this data source is denoted the International Money Market Service (MMS). Among the recent papers using this dataset, there are Andersen et al. (2003 and 2004), Balduzzi et al. (2001), and Christiansen and Ranaldo (2005). The previous literature shows that the announcement days are spread out almost evenly across the different days of the week.

which we have access to the high frequency data, namely from May 1988 to May 2003. Table 5 shows the list of the news bulletins, the periods of the announcement dates, the frequency of releases (monthly, each six-week, or quarterly) and time of day of the announcement dates.

In accordance with previous literature, we use the standardised news for announcement k:

$$S_{k,t} = \frac{A_{k,t} - E_{k,t}}{\sigma_k} \tag{7}$$

Where $A_{k,t}$ ($E_{k,t}$) is the realised (expected) value for announcement k at time t. σ_k is the standard deviation of the announcement surprise ($A_{k,t} - E_{k,t}$) across the entire sample. The frequency of daily extremes conditional on the news announcements is compared with non-announcement probability for the same time of day. The length and composition of non-announcement samples is consistent with the announcement data.[8]

4.1 Announcement Effect

All these news bulletins are pre-scheduled. Thus, we can simply calculate the frequency of daily extreme prices. We consider a news announcement accountable for a daily extreme if the highest or lowest traded price falls within 15 minutes of the release time. The extreme of this 15-minute window time is compared with all traded prices during the CBOT trading hours (for bond futures), the CME outcry time elongated by the last trading hour at the Globex (for equity futures) and from 8 a.m. to 5 p.m. on the currency market. Exchange rates are traded round-the-clock. We decided to limit the comparative time to the US working time (i.e. from 8 a.m. to 5 p.m.) rather than over 24 hours, since it better captures the US currency market reaction to US news bulletins. We also considered using other time intervals[9] to assess the market reaction. However, previous literature found that a 15-minute period encompasses the typical market response (see, e.g. Andersen et al. (2003, 2004), Balduzzi et al. (2001)).

The following picture clearly emerges from Table 5. First, various pre-schedule news announcements significantly (at least at 5% of significance level)

[8] For instance, in January 1997 business inventory announcement was moved from 10:00 to 8:30 a.m. EST. The related non-announcement sample matches this change.

[9] In particular, we considered 15, 30, 45 and 60-minute intervals. We also analyzed how frequent the extreme price of the one hour after the news announcement occurs within the 15 minutes after the announcement time. For the currency market, we also used a 24-hour comparative time to determine the extreme of the day. The results are largely consistent with those presented in this paper.

increase the incidence of extreme prices. The futures on the treasury notes are the most responsive to news events. In the case of 19 out of 24 news items, the occurrence of daily extremes (highs and lows taken together) increases significantly. The few minutes after the release of GDP Advance, Nonfarm Payrolls, Producer Price Index and Unemployment Rates embrace the daily extreme price in almost 6 out 10 releases. However, CHF/USD exchange rates and S&P futures are also considerably affected by the news announcements. For 10 news bulletins, the probability of daily extremes in these two assets rises significantly. The most influential news items seem to be the Unemployment Rate, Nonfarm Payrolls and Consumer Price Index. Unemployment Rate and Nonfarm Payrolls releases originate 56–58% of price extremes in S&P futures and 37–38% of the furthest spot rates in the CHF/USD market. Trade balance announcements also impact significantly on currency spot rates (28% of the extremes). Consumer Confidence Index and GDP Advance announcements form more than 41% of the extremes in S&P futures. The high sensitivity of the equity market to news announcements contrasts with the previous literature (e.g. Andersen et al. (2004), Christiansen and Ranaldo (2005)), indicating that macroeconomic news has a weaker impact on equity markets in terms of price and volatility.

Second, news announcements seem to impact rather symmetrically on high and low prices, although low prices seem more connected with news releases. In the case of the treasury yields, the probability that a news announcement could significantly engender a low (high) price holds for 21 (18) news items. In the case of S&P futures, lows (highs) after news releases are more likely for 11 (10) information items. On average, news announcements generate 21% (18%) and 11% (10%) of highs (lows) in treasury notes and S&P futures. However, an opposing picture is true of the currency market where news announcements are more related to high rather than low prices.

4.2 News effect

The information content of a news announcement rather than its release time may characterise the formation of extreme prices. To see this, we analyse whether the surprise or unexpected value of announcement k released in day t has an impact on the extreme price of that day. More precisely, we perform the following LS regressions based on Newey and West (1987) standard errors:

$$\Delta p_t^H = \alpha_k + \beta_k \Delta p_{t-1}^H + \theta_k S_{k,t} + \epsilon_t \tag{8}$$

The dependent variable, Δp_t^H, is the (log) price change from the high of the day prior to the news announcement to the high of the release day. For practical reasons, we multiply Δp_t^H by 1,000. $S_{k,t}$ is the standardised surprise component in the news item k announced at time t. ϵ_t is the residual term. The same approach holds for low-to-low price changes, Δp_t^L.

Table 6 and 7 show the main findings for high and low prices respectively. In many cases, news exerts a statistically significant influence on the formation of extreme prices. The unanticipated shocks to fundamentals affect exchange rates, equities and bonds. The bond and equity markets appear as the most and least reactive ones. In 9 (3) of the 23 (22) bulletins, news surprises significantly shape the formation of the high price of treasury notes (S&P) futures. Results on low prices are similar. Again, Nonfarm Payrolls and Unemployment Rates are among the most influential bulletins. However, Retail Sales, New Home Sales, ISM and Consumer Confidence also have an impact. The general pattern is that "good news" tends to produce dollar appreciation and price corrections in equity and bond markets. As discussed in Andersen et al. (2003, 2004[10]), the currency reaction is consistent with a variety of models of exchange rates determination, central banks' reaction function and recent empirical findings. The discounted cash flow method is a simple but straight-forward way to discover why "good news" is perceived as "bad news" in equity and bond valuation. The bond price is inversely related to nominal risk-free interest rate. Thus, inflationary and real shocks should decrease bond prices. Empirical support of this view is provided in Balduzzi, Elton and Green (2001), for example. The situation is different for equity values. Equity values can be loosely divided into three components: the risk-free interest rate, expected future cash flows and equity risk premium. As for bonds, a positive real shock exerts a negative effect on equity prices by increasing the interest rate. The same real shock, however, impacts positively on expected future cash flows. The effect on risk premium is uncertain. Thus, the final impact on equity prices is elusive. The same transmission mechanism holds for inflationary shocks. This may explain why equities show the weakest link with fundamentals. Another interesting result from Table 6 and 7 is that news announcements tend to interrupt the autoregressive pattern in high-to-high and low-to-low returns. The positive autoregressive coefficients that were highly significant overall weaken or even suspend their effect during information events. This suggests that news releases represent shocks and act as temporary breaks in the extreme price behaviour.

One pertinent question is whether macroeconomic announcements impact differently across business cycles. After all, market participants may attach

[10] Andersen et al. (2004) use a two-country general equilibrium model to discern how macroeconomic news impact on foreign exchange, bond and equity prices.

different meanings to or make different interpretations for the same news item in different economic regimes. For instance, good news from Retail Sales announcements may be interpreted as a promising sign of economic recovery during recessions, but a worrisome indication of overheating that may eventually turn into a more restrictive monetary policy in expansions. This speaks in favour of conditioning the news impact analysis to economic regimes. To do this, we transform equation (7) as follows:

$$\Delta p_t^H = \alpha_k + \beta_k \Delta p_{t-1}^H + \beta_k^* R_t \Delta p_{t-1}^H + \theta_k S_{k,t} + \theta_k^* R_t S_{k,t} + \epsilon_t \tag{9}$$

R_t is a recession indicator which is equal to one when the US economy is in recession as defined by the NBER business cycle data. We decided to limit our analysis to bond futures since they cover a sample period including two representative contraction periods, namely the recession periods are from 1 July 1990 to 28 February 1991 and again from 1 March 2001 to 31 October 2001.

The main findings on the conditional analysis are summarised in Table 8. Taken in absolute terms, the size effect of news surprises is stronger in expansions, i.e. $|\theta_k| > |\theta_k + \theta_k^*|$. Second, news surprises have a different impact across economic regimes. θ_k is generally negative and θ_k^* is positive. Looking at the coefficient significance, "good news" has a significant negative impact in expansions, but not in recessions. There results are in line with other findings in recent literature. Boyd, Hu and Jagannathan (2005) find that bond prices rise as reaction to bad labour market news only in the case of expansions. They argue that the way market participants attach significance to the diverse value drivers is state-dependent. Unemployment news must convey more information about the interest rates (risk premiums and expected future cash flows) in expansions (recessions). Andersen et al. (2004) also find an opposite market reaction across business cycles. They suggest that discount rates (cash flows) tend to be the dominating value factor during expansions (contractions). Our results on extreme prices are in line with this view. News impacts appear to be state-dependent. A positive surprise tends to shift high and low prices downward in expansions, but it tends to leave extreme boundaries unaffected in contractions.

5 Modelling high and low asset prices

5.1 Econometric framework

The Granger Representation Theorem (Engle and Granger (1987)) establishes that cointegrated variables have three equivalent representations: a vector autoregression model (VAR) in levels, a vector error correction (VEC) model, and a vector moving average (VMA) representation. Let us take a 2 x 1 VAR(k) (nonstationary) representation at level where $\mathbf{p}_t = \left(p_t^H, p_t^L\right)'$:

$$\mathbf{p}_t = c + \sum_{k=1}^{K} \mathbf{A}_k \mathbf{p}_{t-k} + \mathbf{e}_t \tag{10}$$

$$\mathbf{e}_t = (e_{1,t}, e_{2,t})' \sim iid\,(0, \sum) \tag{11}$$

$$\sum = \begin{bmatrix} \sigma_1^2 & \sigma_{2,1} \\ \sigma_{1,2} & \sigma_2^2 \end{bmatrix} \tag{12}$$

The $\mathbf{p}_t$ has the reduced form VEC representation of order $(K-1)$:

$$\Delta\mathbf{p}_t = \alpha\left(\beta'\mathbf{p}_{t-1} - \mu\right) + \sum_{k=1}^{K-1} \Gamma_k \Delta\mathbf{p}_{t-k} + \mathbf{e}_t \tag{13}$$

Where

$$\alpha\beta' = -\mathbf{A}(1) = -\left(\mathbf{I}_2 - \sum_{k=1}^{K} \mathbf{A}_k\right) \tag{14}$$

$$\mathbf{\Gamma}_k = \sum_{j=k+1}^{K} \mathbf{A}_j \tag{15}$$

$$\mu = E\left(\beta'\mathbf{p}_{t-1}\right) \tag{16}$$

The term μ captures systematic differences in the high and low prices and can be interpreted as the constant or long-run range. α is a $2x1$ vector of error correction coefficients that measure each price's expected speed in eliminating the high-low deviation or the temporary range fluctuation from equilibrium values.

Stock and Watson (1988) show that each cointegrated price for the same underlying asset is composed of an unobservable, common fundamental value, a transitory error, and a constant. In the spirit of Hasbrouck (1995), the common trend represents the efficient price behaving as a random walk. The transitory error refers to any digression from the true, unobservable price. From this perspective, the constant in the error correction equation reflects any non-stochastic difference between high and low prices. More formally, we state that the high and low prices are cointegrated with the cointegrating vector $\beta = (1, -1)$ if $\beta' \mathbf{p}_{t-1}$ is $I(0)$. The cointegrating error $\beta' \mathbf{p}_{t-1}$ is the discrepancy between the two extreme prices and is corrected over time.

We propose modelling high and low prices on the basis of a simple vector autoregressive and cointegrating model with a $2x1$ vector of log prices $\mathbf{p}_t = \left(p_t^H, p_t^L\right)'$, as follows:

$$\Delta p_t^H = \left(1 p_{t-1}^H - \beta p_{t-1}^L - \mu\right) \alpha_1 + \sum_k \gamma_{1,k} \Delta p_{t-k}^H + \sum_k \lambda_{1,k} \Delta p_{t-k}^L + \epsilon_{1,t} \quad (17)$$

$$\Delta p_t^L = \left(1 p_{t-1}^H - \beta p_{t-1}^L - \mu\right) \alpha_2 + \sum_k \gamma_{2,k} \Delta p_{t-k}^H + \sum_k \lambda_{2,k} \Delta p_{t-k}^L + \epsilon_{2,t} \quad (18)$$

where Δp_t^H (Δp_t^L) is the logarithmic high-to-high (low-to-low) price change between t and $t-1$, and $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are the residuals for the high and low equation, respectively. This is the most basic specification for modelling high and low prices in this setting. Of course, many extensions are possible, and the use of exogenous variables is conceivable (e.g. see above the influential role of information announcements). Furthermore, this technique can be generalised to n-price variables where cointegrating characteristics of high, low, close, and open prices are considered. However, these ideas go beyond the research purposes of this paper.

5.2 Empirical analysis

We conduct the Akaike Information Criterion (AIC) test to assess the appropriate lag length for the lag order of the VAR. The results of the AIC (not tabulated) indicate that 1, 3 and 5 lags are the opportune lengths for the monthly, daily and hourly implementation of the VAR model, respectively.

Table 9 shows the results of the estimation of the VECM models over the entire sample periods. To estimate the VECM in this paper, we use the common cointegration methodology based on the maximum likelihood procedure proposed by Johansen (1988). The residual test shows serially uncorrelated but non-normal residuals for daily regressions. For the monthly regressions, residual are closer to the Gaussian distribution. Theoretical arguments (e.g. Gourieroux et al. (1984)) suggest that in this empirical setting, the Pseudo Maximum Likelihood principle applies.

First, we note that the coefficients of determination (R-squares) are fairly high for all time granularities and assets. Intraday estimations provide the highest R-squares (from 14% to 24%) and monthly regressions the smallest ones (5%-20%). The S&P futures index shows the best goodness of fit. Looking at the high and low regression equations separately, we observe that the higher R-squares belong to the low equation only for the hourly timeframe; for longer timeframes, the high equation has higher coefficients of determination. High R-squares go hand in hand with the t-statistics of the autoregressive coefficients in the VARs; therefore, higher R-squares normally correspond to a longer dependence on past data. This raises the question of whether the asymmetries between high and low prices can be related to leverage effects and short-sale constraints.

We observe that, as expected, all the estimated βs in the normalised cointegration equation are very significant and very close to one. This result bears out the cointegration hypothesis. In principle, it also allows us to impose the restriction $\beta = 1$. The VECM implementations restricted in this way provide estimates that are slightly more significant (in particular, a larger number of estimated coefficients significantly different from zero and higher R-squares). But we decided to present the unrestricted estimates. As discussed above, α represents the speed of the adjustment when high and low prices deviate from their long-run values. It is worth noting that for the S&P index, low prices tend to adjust faster for any time granularity (that is, $|\alpha_1| < \alpha_2$). The opposite holds for futures on treasury notes (that is, $|\alpha_1| > \alpha_2$). In this case, high prices always seem to adjust more promptly. For the currency asset, the results are mixed: high prices are more responsive on an hourly and daily basis but not on a monthly basis.

The vector autoregressive framework allows analysis of the impulse-response function. We use the generalised impulses proposed by Pesaran and Shin (1998) to construct an orthogonal set of innovations that does not depend on the VAR ordering. The impulse-response function shows how high and low prices react to a typical shock (one standard deviation size) coming from high and low prices. Figures 3 and 4 show the impulse-response analysis for the daily and monthly shocks in the S&P 500 index future market. In general, the following patterns are observable: First, a low-price shock has an immediate and greater impact. This evidence holds for all timeframes and assets. There are a number of possible explanations for this asymmetric impact on high- and low-price innovations. One is that a trade or news impact which shifts the lower boundary of a resistance level engenders a stronger and faster reaction. This could be due to traders' overreactions or to stop-loss orders. In this respect, Osler (2005) shows that large exchange-rate changes are catalysed by stop-loss orders which create rapid, self-reinforcing price movements. Second, any shock impact has a more lasting effect on the high-price levels (say, 10 periods ahead) for S&P index futures. In the long run, however, shocks affect more low-price levels for treasury yields futures. For the currency market the results are mixed, and are in line with the speed of adjustment represented by $|\alpha_1|$ and α_2. Finally, hourly and daily shocks typically engender a reversal pattern. This pattern can be decomposed in an immediate and successive reaction. The immediate reaction consists of a large impact in the first period that continues marginally in the subsequent one or two periods. In the subsequent phase, the impact reverts in periods 3-6 ahead and then converges towards its long-run level. The monthly shocks, however, are more gradual and smoothed, and do not present reversal patterns. The greater reaction in the short run may be attributable to the bid-ask spread enlargement or to a temporary short-term overreaction.

6 Analysis of the VECM model

The VECM model presented above was used to calculate out-of-the-sample forecasts. The forecasting analysis was performed on a daily and monthly basis.[11] The daily and monthly regressions are based on 250 and 60 observations, respectively. This means that we use one year and five years of the past observations to estimate the regression coefficients to be used for the next predictions over daily and monthly periods, respectively. Other estimation periods have been tested. These periods represent a fair compromise, guaranteeing reasonable stability and precision. Each forecast is obtained using these observation numbers. This means that we adopt a "rolling-ahead" procedure: once we estimate a regression, we calculate the prediction for the next high and low prices and then move one period ahead by losing the first observation of the previous estimation period. We obtain 3000 out-of-the-daily-sample forecasts. For the monthly predictions, we have 72, 96 and 115 out-of-the-sample forecasts for CHF/USD exchange rates, S&P index futures and treasury yield futures, respectively.

Table 10 shows some simple tests to assess how these predictions fit with real data. We employ two main methods: hit ratios and regressions. Hit ratios evaluate the extent to which forecasts are able to predict future actual data. Table 10 presents four hit ratios. Two of them measure how many times the

[11] Intraday forecasting possibly only attracts the attention of a minority of the financial community. Also, intraday forecasting could imply an adjustment for time-of-day seasonalities and further microstructure issues. For these reasons, we have decided to not present hourly forecasts.

forecasts predict the correct direction of future price changes, which are the high-to-high and low-to-low returns. The other two hit ratios measure how many times the actual price lies within the predicted high and low prices. We use two different types of actual prices: the last price (corresponds to the closing price for daily data and the last traded price of the month for monthly data) and the mid-price between the first and last prices of a given trading period. The mid-price is simply the sum of the first and last prices divided by two. We refer to these two frequency measures as "close-price-within-range" and "mid-price-within-range". We have considered other price definitions and points of time.[12]

To provide a benchmark to the VECM forecasts, we define a naïve forecasting strategy based on past data. This forecasting procedure simply consists of using the earliest high and low prices. For example, the naïve high-to-high forecast on a daily basis implies that the price direction from yesterday's to today's high determines the price direction from today's to tomorrow's high. By the same token, the naïve prediction for today's range is yesterday's range. We use the Diebold and Mariano (1995) method to test the null hypothesis of no difference in the accuracy between the naïve and VECM forecasts.

According to the hit ratios, high and low forecasts are able to predict fairly well the next high and low price movements. High-to-high and low-to-low returns suggest that VECM predictions capture the correct direction of future price movements. The close-within-range and mid-price-within-range ratios show that we can enhance significantly the prediction precision of future prices using VECM forecasts. It is worth noting that the mid-price prediction is always better that the close price forecast. This is because the last or close prices are more affected by extreme prices (see the discussion on the arc-sine law for more details).

The second method for testing the goodness of these forecasts is to regress the actual range on the forecast one.[13] We perform a simple linear least-square regression where the dependent variable is the actual range and the explanatory variables are the forecast range and a constant. We also account for heteroskedasticity and residual autocorrelation by using the Newey-West adjustments for the standard errors and covariance. Table 10 shows that the estimated

[12] For instance, we have considered the midday price (which corresponds to the nearest trading price around midday for daily data and in the middle of the month for monthly data) and a randomly selected trading price within the time interval. To randomly select trading prices, we broke up the trading day into 5-minute intervals and randomly selected one of these 5-minute periods. All these tests confirm our main results.

[13] We also used the regression approach to analyse high and low forecasts separately. In particular, we analyse the high-to-high and low-to-low price changes. These further results (available upon request) largely confirm the regression analysis on the range.

coefficients relating the VECM forecast and the actual ranges (called beta) are always extremely significant (less than 1% of significance level) and near one, whereas the constant is negligible. More important, the Chi-square values related to Wald test for the null hypothesis that beta is equal to one can never be rejected. The R-squares of these regressions are also appreciable; the lowest R-square is for the monthly treasury yield regression (10%) while the highest R-square, which is for the S&P index, reaches 50%. These results can be compared with the naïve forecasting strategy that consists of using the last observed range to predict the next range. Table 10 clearly shows that the naïve autoregressive approach based on past data provides less precise predictions. All the tests mentioned above support this outcome: the Wald test always suggests a beta significantly different from one, the R-squares are much lower and the root-mean-square error (RMSE) is always higher. These results suggest that vector autoregressive modelling with error correction is able to capture the information contents of high and low prices for prediction purposes.

7 Conclusion

This research explores the information content of extreme prices in financial markets. We provide evidence that extreme prices are characterised by a number of relevant stylised facts that hold true across asset classes and time granularities. These stylised facts are the following: First, high and low prices tend to cluster at the very beginning or end of a time interval if long (typically monthly) time intervals are considered. Within shorter timeframes (typically daily), the location of high and low prices is characterised by microstructure and behavioural aspects such as overnight non-trading time, trading intensity in the different regions around the clock and scheduled announcements of relevant news bulletins. Second, extreme prices in the current period depend on the extreme prices of previous periods. This evidence suggests sticky movements from farthest price steps and resistance levels. These autocorrelated movements also characterise the joint behaviour of high and low prices, i.e. the range. Third, the comovement of high and low prices is resilient in the short run but steadily convergent in the long run. This means that time-varying market uncertainty and microstructure issues can make high and low prices deviate temporarily apart while transient divergences revert towards a long-run range.

Second, this research shows that extreme prices depend on the time and information content of news announcements. On the one hand, extremes of the day cluster in the few minutes after news announcements. Unemployment

Rate, Nonfarm Payrolls and Consumer Price Index bulletins elicit the occurrence from 26% up to 58% of the daily extremes. On the other hand, the unexpected component in the news announcement exerts a significant impact on extreme price formation. "Good news" tends to move the high-low boundaries upward in foreign exchanges and downward in equity and bond futures. Conditioning the bond futures' reaction to business cycles, we note that news effects may differ across economic regimes.

The third main contribution of this research is to provide evidence of the predictability of extreme prices. We propose a simple way to model high and low prices: the vector autoregressive model with error correction. This econometric implementation fits with all the stylised facts mentioned above, namely autoregression, cointegration and interdependence. Some evidence of the high predictive power of VECM is provided.

The relevance of a better understanding of the information content of extreme prices crosses many fields in finance and economics. It goes far beyond mere speculative use. The stylised facts documented in this research can be used in many domains and for many other purposes, in particular risk analysis and management (e.g. hedging, portfolio insurance and guaranteed products) as well as derivatives (e.g. exotic options). In more general terms, however, valuable indications of extreme prices can be very helpful in many aspects of the decision-making process, e.g. as a timing indicator and in scenario analysis. Future research should also compare the predictive power of different volatility models, in particular GARCH, realised volatility, implied volatility, and range-based volatility models across different time granularities. All these issues go beyond our research purposes. We leave a systematic examination of these issues for upcoming research.

References

[1] Acar, E. and R. Toffel (1999), Highs and Lows: Times of the Day in the Currency CME Market, Chapter 5 in Financial Markets Tick by Tick, edited by Lequex, P., John Wiley and Sons.

[2] Alizadeh, S., M. W. Brandt and F. X. Diebold (2002), Range-Based Estimation of Stochastic Volatility Models, Journal of Finance 57, 1047-1091.

[3] Andersen, T. G., and T. Bollerslev (1998), Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts, International Economic Review 39, 885-905.

[4] Andersen, T. G., T. Bollerslev, F. X. Diebold and C. Vega (2003), Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange, American Economic Review 93, 38-62.

[5] Andersen, T. G., T. Bollerslev, F. X. Diebold and C. Vega (2004), Real-Time Price Discovery in Stock, Bond, and Foreign Exchange Markets, Working Paper, Concordia University.

[6] Balduzzi, P., E. J. Elton and T. C. Green (2001), Economic News and Bond Prices: Evidence from US Treasury Market, Journal of Financial & Quantitative Analysis 36, 523-543.

[7] Ball, C. A., and W. N. Torous (1984), The Maximum Likelihood Estimation of Security Price Volatility: Theory, Evidence, and Application to Option Pricing, Journal of Business 57, 97-112.

[8] Beckers, S. (1983), Variances of Security Price Returns based on High, Low, and Closing Prices, Journal of Business 56, 97-112.

[9] Bollerslev T., J. Cai and F. M. Song (2000), Intraday Periodicity, Long Memory Volatility, Macroeconomic Announcements Effects in US Treasury Bond Market, Journal of Empirical Finance 7, 37-55.

[10] Boyd, J. H., J. Hu and R. Jagannathan (2005), The Stock Market's Reaction to Unemployment news: Why Bad news Is Usually Good for Stocks, Journal of Finance 60, 649-672.

[11] Brandt, M. W., and F. X. Diebold (2006), A No-Arbitrage Approach to Range-Based Estimation of Return Covariances and Correlations, Journal of Business 79, 61-73.

[12] Brock, W. A., and A. W. Kleidon (1992), Periodic Market Closure and Trading Volume, Journal of Economic Dynamics and Control 16, 451-489.

[13] Christensen, K., and M. Podolski (2005), Asymptotic Theory for Range-Based Estimation of Integrated Variance of a Continuous Semi-Martingale, Working Paper, Swiss National Bank.

[14] Christiansen, C., and A. Ranaldo (2005), Realized Bond-Stock Correlation: Macroeconomic Announcement Effects, Working Paper, Aarhus School of Business.

[15] Chung K. H., F. Van Ness and R. Van Ness (1999), Limit Orders and Bid-Ask Spread, Journal of Financial Economics 53, 255-287.

[16] DeGrauwe, P., and D. Decupere (1992), Psychological Barriers in the Foreign Exchange Markets, Journal of International and Comparative Economics 1, 87-101.

[17] Diebold, F. X., and R. S. Mariano (1995), Comparing Predictive Accuracy, Journal of Business and Economic Statistics 13, 253-263.

[18] Engle, R. F. (1982) Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation, Econometrica 50, 987-1008.

[19] Engle, R. F., and C. Granger (1987), Cointegration and Error Correction Representation, Estimation, and Testing, Econometrica 55, 251-276.

[20] Fama, E. F. (1970), Efficient Capital Markets: A Review of Theory and Empirical Work, Journal of Finance 25, 383-417.

[21] Fama, E. F. (1991), Efficient Capital Markets: II, Journal of Finance 46, 1575-1617.

[22] Feller, W. (1951), The Asymptotic Distribution of the Range of Sum of Independent Variables, Annals of Mathematical Statistics 22 (3), 427-432.

[23] Feller, W. (1968), An Introduction to Probability Theory and Its Applications, Vol. I, Third Edition, Wiley.

[24] Fiess, N., and R. MacDonald (1999), Technical Analysis in the Foreign Exchange Market: a Cointegration-Based Approach, Multinational Finance Journal 3, 147–172.

[25] Fiess, N., and R. MacDonald (2002), Towards the Fundamentals of Technical Analysis: Analysing the Information Content of High, Low and Close prices, Economic Modeling 19, 353–374.

[26] Garman, M. B., and M. J. Klass (1980), On the Estimation of Security Price Volatilities from Historical Data, Journal of Business 53 (1), 67-78.

[27] Goodhart, C., and R. Curcio (1992), When Support / Resistance Levels are Broken, Can Profits Be Made? Evidence from the Foreign Exchange Market, Discussion Paper 142, London School of Economics, Financial Markets Group.

[28] Goodhart, C., R. Ito, and R. Payne (1996), One Day in June 1993: a Study of the Working of the Reuters 2000-2 Electronic Foreign Exchange Markets, edited by J. Frankel, G. Galli and A. Giovannini, Chicago: University of Chicago Press, IL, pp. 107-79.

[29] Gourieroux, C., A. Monfort, and A. Trognon (1984), Pseudo Maximum Likelihood Methods: Theory, Econometrica 52, 681-700.

[30] Hasbrouck, J. (1995), One security, many markets: Determining the contributions to price discovery, Journal of Finance 50, 1175-99.

[31] Hung, A. A., and C. R. Plott (2001), Information Cascades: Replication and Extension to Majority Rule and Conformity-Rewarding Institutions, American Economic Review 91, 1508-1520.

[32] Itô, K., and H. P. Jr. McKean (1974), Diffusion Processes and their Sample Paths, Berlin Heidelberg New York, Springer.

[33] Ito, T., and Y. Hashimoto (2005), Intra-day Seasonality in Activities of the Foreign Exchange Markets: Evidence from the Electronic Broking System, Working Paper.

[34] Johansen, S. (1988), Statistical analysis of cointegration vectors, Journal of Economic Dynamics and Control 12, 231-54.

[35] Kahneman, D., and A. Tversky (1979), Prospect Theory: An Analysis of Decision under Risk Econometrica 47, 263-291.

[36] Lehmann B., and D. Modest (1994), Trading and Liquidity on the Tokyo Stock Exchange: a Bird's Eye View, Journal of Finance 48, 1595-1628.

[37] Lo, A., H. Mamaysky, and J. Wang (2000), Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation, Journal of Finance 56, 1705–1765.

[38] Kunitomo, N. (1992), Improving the Parkinson Method of Estimating Security Price Volatilities, Journal of Business 64, 295-302.

[39] Mandelbrot, B. (1963), The Variation of Certain Speculative Prices, Journal of Business 36, 394-419.

[40] Martens, M., and D. van Dijk (2005), Measuring Volatility with the Realized Range, Working Paper, Erasmus University Rotterdam.

[41] Menkhoff, L. (1998), The Noise Trading Approach: Questionnaire Evidence from Foreign Exchange, Journal of International Money and Finance 17, 547–564.

[42] Newey, W., and K. West (1987), A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica 55, 703-708.

[43] Olsen, R. B., A. U. A. Müller, M. M. Dacorogna & O. V. Pictet & R. R. Davé & D. M. Guillaume (1997), From the bird's eye to the microscope: A survey of new stylised facts of the intra-daily foreign exchange markets, Finance & Stochastics 1, 95-129.

[44] Osler, C. L. (2000), Support for Resistance: Technical Analysis and Intraday Exchange Rates, Economic Policy Review 6, 53-68.

[45] Osler, C. L. (2005), Stop-loss Orders and Price Cascades in Currency Markets, Journal of International Money and Finance 24, 219-242.

[46] Parkinson, M. (1980), The Extreme Value Method for Estimating the Variance of the Rate of Return, Journal of Business 53, 61-65.

[47] Pesaran, M. H., and Y, Shin (1998), Impulse Response Analysis in Linear Multivariate Models, Economics Letters 58, 17-29.

[48] Revuz, D., and M. Yor (1999), Continuous Martingales and Brownian Motion, Third Edition, Springer.

[49] Rogers, L. C. G., and S. E. Satchell (1991), Estimating Variances from High, Low, and Closing Prices, Annals of Applied Probability 1, 504-512.

[50] Stock, J. H., and M. W. Watson (1988), Testing for Common Trends, Journal of the American Statistical Association 83, 1097-1107.

[51] Yang, D., and Q. Zhang (2000), Drift-Independent Volatility Estimation Based on High, Low, Open, and Close Prices, Journal of Business 73, 477-491.

Table 1: Summary Statistics

This table shows the summary statistics for several definitions of (log) price changes, namely between two prices at the end of two successive periods (CC), from the previous to the next high price (HH), from the first to the high price (FH), from the previous to the next low price (LL), from the first to the low price (FH), and the (log) difference between high and low price of a given period (RANGE). Three timeframes are considered: hours, days, and months. Three representative assets are analysed: the CHF/USD spot exchange rate (CHF/USD), futures on the S&P 500 index (SP) and futures on treasury notes (TY). The sample period for CHF/USD extends from the beginning of 1993 to the end of May 2003; the sample period for SP and TY is from 7 November 1988 to the end of May 2003.

CHF/USD	**Hour**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.000	0.000	0.001	0.000	-0.001	0.001
Median	0.000	0.000	0.001	0.000	-0.001	0.001
Maximum	0.032	0.032	0.023	0.031	0.000	0.023
Minimum	-0.035	-0.035	0.000	-0.035	-0.019	0.000
Std. Dev.	0.001	0.001	0.001	0.001	0.001	0.001
Skewness	-0.220	0.292	3.140	-0.832	-3.275	3.140
Kurtosis	24.2	30.4	25.3	29.6	24.0	25.3

SP	**hour**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.000	0.000	0.002	0.000	-0.002	0.002
Median	0.000	0.000	0.001	0.000	-0.001	0.001
Maximum	0.040	0.054	0.055	0.035	0.000	0.055
Minimum	-0.063	-0.057	0.000	-0.067	-0.046	0.000
Std. Dev.	0.004	0.003	0.002	0.004	0.003	0.002
Skewness	-0.253	0.389	3.794	-0.868	-2.992	3.794
Kurtosis	15.6	20.2	38.2	17.5	19.7	38.2

CHF/USD	**day**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.000	0.000	0.005	0.000	-0.005	0.005
Median	0.000	0.000	0.004	0.000	-0.004	0.004
Maximum	0.037	0.036	0.040	0.039	0.000	0.040
Minimum	-0.035	-0.040	0.000	-0.037	-0.041	0.000
Std. Dev.	0.007	0.006	0.004	0.006	0.005	0.004
Skewness	-0.12	-0.06	1.74	-0.36	-2.07	1.74
Kurtosis	5.4	6.1	7.7	6.8	10.3	7.7

SP	**day**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.000	0.000	0.006	0.000	-0.007	0.006
Median	0.001	0.000	0.004	0.001	-0.005	0.004
Maximum	0.076	0.052	0.086	0.078	0.000	0.086
Minimum	-0.093	-0.047	0.000	-0.075	-0.086	0.000
Std. Dev.	0.011	0.009	0.006	0.011	0.007	0.006
Skewness	-0.15	0.07	2.93	-0.14	-2.45	2.93
Kurtosis	8.2	6.3	22.1	8.4	14.7	22.1

CHF/USD	**month**					
	CC	HH	FH	LL	FL	RANGE
Mean	-0.001	-0.001	0.024	-0.001	-0.026	0.024
Median	0.000	0.002	0.020	0.004	-0.022	0.020
Maximum	0.064	0.060	0.076	0.060	-0.001	0.076
Minimum	-0.090	-0.065	0.000	-0.098	-0.100	0.000
Std. Dev.	0.030	0.026	0.017	0.029	0.020	0.017
Skewness	-0.19	-0.34	0.74	-0.52	-1.02	0.74
Kurtosis	2.6	2.6	3.2	3.3	3.8	3.2

SP	**month**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.006	0.006	0.035	0.007	-0.037	0.035
Median	0.015	0.004	0.030	0.006	-0.026	0.030
Maximum	0.111	0.078	0.124	0.174	0.000	0.124
Minimum	-0.126	-0.093	0.001	-0.207	-0.247	0.001
Std. Dev.	0.044	0.031	0.026	0.050	0.040	0.026
Skewness	-0.53	-0.45	0.99	-0.86	-2.15	0.99
Kurtosis	3.5	3.7	3.8	7.1	9.1	3.8

TY	**hour**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.000	0.000	0.001	0.000	-0.001	0.001
Median	0.000	0.000	0.001	0.000	-0.001	0.001
Maximum	0.019	0.018	0.020	0.016	0.000	0.020
Minimum	-0.117	-0.113	0.000	-0.117	-0.017	0.000
Std. Dev.	0.002	0.002	0.001	0.002	0.001	0.001
Skewness	-14.44	-13.65	3.50	-15.37	-3.35	3.50
Kurtosis	1028	991.8	31.0	1068.3	25.9	31.0

TY	**day**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.000	0.000	0.002	0.000	-0.002	0.002
Median	0.000	0.000	0.002	0.000	-0.002	0.002
Maximum	0.019	0.019	0.020	0.015	0.000	0.020
Minimum	-0.119	-0.114	0.000	-0.120	-0.022	0.000
Std. Dev.	0.004	0.004	0.002	0.004	0.002	0.002
Skewness	-5.88	-5.38	1.71	-6.53	-2.06	1.71
Kurtosis	156.8	142.2	7.6	178.6	9.6	7.6

TY	**month**					
	CC	HH	FH	LL	FL	RANGE
Mean	0.001	0.001	0.014	0.001	-0.014	0.014
Median	0.002	0.003	0.012	0.004	-0.010	0.012
Maximum	0.046	0.042	0.047	0.039	0.000	0.047
Minimum	-0.126	-0.142	0.000	-0.127	-0.126	0.000
Std. Dev.	0.020	0.019	0.010	0.018	0.015	0.010
Skewness	-1.67	-2.47	0.80	-2.37	-3.23	0.80
Kurtosis	11.7	19.7	3.4	18.0	21.2	3.4

Table 2: Autocorrelation Function

This table shows the autocorrelation function for several definitions of (log) price changes, namely between the two prices at the end of two successive periods (CC), from the previous to the next high price (HH), from the first to the high price (FH), and the (log) difference between high and low price of a given period (RANGE). Three timeframes are considered: hours, days, and months. Three representative assets are analysed: the CHF/USD spot exchange rate (CHF/USD), futures on the S&P 500 index (SP) and futures on treasury notes (TY). The horizontal line represents the order lags. The significance levels are based on the p-values of the Ljung-Box Q-statistics. ** (*) means a rejection of the null hypothesis that there is no autocorrelation at least at 1% (5%) probability.

CHFUSD Hour	1	2	3	4	5	6	7	8	9	10	11	12
CC	0.00	0.00	-0.01	-0.01*	0.00	0.00	0.00	0.00	0.00	-0.01	0.00*	0.00
HH	0.14**	-0.01**	-0.02**	-0.01**	0.00**	0.01**	0.00**	0.00**	-0.01**	-0.02**	-0.02**	-0.01**
FH	0.26**	0.19**	0.13**	0.10**	0.08**	0.06**	0.03**	0.01**	-0.02**	-0.06**	-0.08**	-0.08**
Range	0.26**	0.19**	0.13**	0.10**	0.08**	0.06**	0.03**	0.01**	-0.02**	-0.06**	-0.08**	-0.08**
CHFUSD Day												
CC	-0.06**	0.04**	-0.03**	0.01**	-0.02**	0.00**	0.01**	0.02**	-0.01**	-0.01**	0.01*	-0.02*
HH	0.10**	-0.06**	0.00**	0.01**	-0.05**	0.01**	0.08**	0.01**	-0.05**	0.00**	-0.03**	-0.03**
FH	0.05*	0.04**	0.00**	0.00*	0.00*	0.07**	0.13**	0.06**	-0.02**	-0.01**	0.02**	0.03**
Range	0.05*	0.04**	0.00**	0.00*	0.00*	0.07**	0.13**	0.06**	-0.02**	-0.01**	0.02**	0.03**
CHFUSD Month												
CC	0.08	-0.07	-0.02	-0.07	0.02	-0.04	0.07	0.06	0.22	0.07	0.00	0.06
HH	0.11	-0.01	0.00	-0.10	-0.02	0.08	0.04	0.19	0.11	0.09	0.09	-0.06
FH	-0.04	-0.11	0.04	-0.04	0.10	-0.04	-0.10	0.10	0.14	-0.04	-0.13	0.04
Range	-0.04	-0.11	0.04	-0.04	0.10	-0.04	-0.10	0.10	0.14	-0.04	-0.13	0.04
SP Hour												
CC	0.00	0.00	0.01	0.03**	0.01**	0.02**	0.01**	-0.04**	-0.03**	0.00**	0.00**	-0.01**
HH	0.04**	-0.02**	0.02**	0.04**	0.04**	-0.02**	0.00**	0.03**	-0.05**	-0.03**	0.01**	0.02**
FH	0.20**	0.15**	0.18**	0.21**	0.17**	0.12**	0.13**	0.20**	0.11**	0.12**	0.15**	0.16**
Range	0.20**	0.15**	0.18**	0.21**	0.17**	0.12**	0.13**	0.20**	0.11**	0.12**	0.15**	0.16**
SP Day												
CC	-0.04*	-0.05**	-0.02**	0.02**	-0.04**	-0.02**	-0.03**	0.03**	0.00**	-0.02**	0.04**	0.02**
HH	0.10**	-0.03**	-0.01**	-0.01**	-0.01**	-0.04**	-0.03**	0.01**	0.02**	0.01**	0.01**	0.05**
FH	0.14**	0.13**	0.12**	0.15**	0.15**	0.16**	0.10**	0.14**	0.14**	0.13**	0.13**	0.15**
Range	0.14**	0.13**	0.12**	0.15**	0.15**	0.16**	0.10**	0.14**	0.14**	0.13**	0.13**	0.15**
SP Month												
CC	-0.04	-0.04	0.03	-0.03	0.09	-0.05	0.02	0.09	0.09	0.14	0.02	0.07
HH	0.28**	0.06**	0.05**	0.06**	-0.01*	0.00*	0.13*	0.24**	0.22**	0.14**	0.12**	0.06**
FH	0.10	0.05	0.10	0.03	0.14	0.09	0.07	0.10	0.18	0.14*	0.10*	0.15*
Range	0.10	0.05	0.10	0.03	0.14	0.09	0.07	0.10	0.18	0.14*	0.10**	0.15**
TY Hour												
CC	0.00	0.00	0.02	0.02*	0.01*	0.02**	0.00**	-0.02**	0.00**	0.00**	0.01**	0.01**
HH	0.04**	0.00**	0.00**	0.02**	0.02**	0.00**	0.01**	-0.02**	0.01**	0.00**	-0.01**	0.01**
FH	0.12**	0.07**	0.05**	0.04**	0.05**	0.05**	0.06**	0.04**	0.03**	0.01**	0.01**	0.03**
Range	0.12**	0.07**	0.05**	0.04**	0.05**	0.05**	0.06**	0.04**	0.03**	0.01**	0.01**	0.03**
TY Day												
CC	0.06	-0.02	-0.04	-0.03*	0.00*	-0.03**	0.02**	-0.03**	-0.01**	0.01**	0.01**	0.04**
HH	0.06**	-0.02**	-0.04**	-0.01**	0.01**	-0.04**	0.00**	0.01**	-0.01**	-0.01**	0.01**	0.03**
FH	0.06**	0.04**	0.00**	0.01**	0.07**	-0.01**	0.07**	0.04**	0.03**	0.03**	0.02**	0.04**
Range	0.06**	0.04**	0.00**	0.01**	0.07**	-0.01**	0.07**	0.04**	0.03**	0.03**	0.02**	0.04**
TY Month												
CC	0.12	-0.07	-0.01	-0.04*	-0.04*	-0.02**	0.10**	-0.04**	-0.04**	0.04**	0.01**	-0.02**
HH	0.14*	-0.04	-0.06	0.03	-0.10	-0.01	0.04	0.07	-0.04	0.01	-0.04	0.03
FH	0.18*	-0.03	0.00	-0.04	0.03	-0.04	0.03	0.03	-0.01	-0.02	0.10	-0.05
Range	0.18**	-0.03	0.00	-0.04	0.03	-0.04	0.03	0.03	-0.01	-0.02	0.10	-0.05

Table 3: Granger Causality

This table shows Granger causality tests for several definitions of (log) price changes, namely between the first and last price of a given trading period (FC), from the first to the high price (FH), from the first to the low price (FO). Three timeframes are considered: hours, days, and months. Three representative assets are analysed: the CHF/USD spot exchange rate (CHF/USD), futures on the S&P 500 index (SP) and futures on Treasury notes (TY). The table shows the F-statistics values of the Granger causality tests. ** (*) means that we can reject the hypothesis of no Granger causality at least at 1% (5%) probability.

	CHFUSD			SP			TY		
	Hour	Day	Month	Hour	Day	Month	Hour	Day	Month
FH not G-C FC	3.06**	2.49*	1.09	7.24**	4.29**	0.47	1.82	1.59	0.41
FC not G-C FH	610.55**	22.77**	3.70**	386.19**	19.68**	17.54**	64.24**	2.25	0.56
FL not G-C FC	2.17*	1.04	1.62	8.06**	1.92	0.16	2.33*	0.95	0.26
FC not G-C FL	453.51**	8.38**	1.15	97.65**	9.77**	0.23	54.18**	3.80**	1.26
FL not G-C FH	878.51**	25.46**	2.08*	459.75**	161.61**	15.62**	109.06**	5.86**	1.10
FH not G-C FL	698.92**	14.38**	0.31	150.09**	33.99**	0.26	107.52**	11.55**	0.12

Table 4: Cointegration test

This table shows the Johansen tests for cointegration between high and low prices assuming no deterministic trends and that the cointegrating equations have intercepts. Three timeframes are considered: hours, days, and months. Three representative assets are analysed: the CHF/USD spot exchange rate (CHF/USD), futures on the S&P 500 index (SP) and futures on Treasury notes (TY). The table shows the eigenvalues and the Likelihood Ratio tests for rejecting the null hypothesis that there is no cointegration. ** (*) means that we can reject the null hypothesis at least at 1% (5%) probability.

	CHF/USD					
	HOUR		DAY		MONTH	
	Eigenv.	LR	Eigenv.	LR	Eigenv.	LR
No CE	0.0907	5992.6**	0.3843	1582.8**	0.1420	20.8*
At most 1	0.0000	2.2794	0.0006	1.9418	0.0107	1.3696

	SP					
	HOUR		DAY		MONTH	
	Eigenv.	LR	Eigenv.	LR	Eigenv.	LR
No CE	0.0445	1189.9**	0.0702	240.6**	0.1782	31.8**
At most 1	0.0001	2.1622	0.0007	2.4490	0.0143	2.1721

	TY					
	HOUR		DAY		MONTH	
	Eigenv.	LR	Eigenv.	LR	Eigenv.	LR
No CE	0.0963	2593.2**	0.0853	330.0**	0.1567	37.4**
At most 1	0.0002	5.2325	0.0014	5.1127	0.0485	8.4443

Table 5: News Announcements and Occurrence of Extremes

This table shows the frequency of daily extreme price within 15 minutes of news announcements. The first column lists the news bulletins. The second and third columns show the period of the announcement dates. The fourth column shows the frequency of news releases (M: month, S: six-week, Q: quarter). The fifth column reports the average of the standardised news surprise. The sixth column shows the time of day on the announcement dates. "High" ("Low") refers to the occurrence of the highest (lowest) price of the trading day. CHF/USD, S&P and TY means the Swiss franc to US dollar spot exchange rate, futures contracts on the S&P 500 Index and futures contracts on the US treasury notes. The last five rows show indicative frequencies of non-announcement intraday periods. ** (*) means that we can reject the null hypothesis of equality in means between announcement and non-announcement samples at least at 1% (5%) probability.

	Periods		Freq.	Surp	CHF/USD		SP		TY	
Announcement	From	To	M/S/Q	Mean	High	Low	High	Low	High	Low
Business Inventory / F	11.88	12.96	M	0.20	4%	6%	4%	3%	4%	5%
Business Inventory / G	01.97	10.03	M	0.15	8%	9%	17%**	11%	18%	24%*
Capacity Utiliz.	11.88	10.03	M	0.11	5%	6%	-	-	10%*	13%**
Construction Spend.	11.88	10.03	M	0.13	3%	8%	2%	5%	13%**	16%**
Cons. Conf. Index	07.91	11.04	M	0.05	3%	9%*	4%	7%	8%*	20%**
Credit	11.88	10.03	M	0.12	1%	1%	2%	3%	-	-
CPI	11.88	11.04	M	-0.11	13%**	13%**	16%**	26%**	28%**	27%**
Durable Goods Ord.	11.88	10.03	M	0.05	10%	6%	11%	14%**	22%*	24%*
Factory Orders	11.88	10.03	M	0.06	9%**	9%*	5%	8%*	7%	10%**
FOMC decisions	11.88	10.03	SW	-0.01	1%	1%	1%	3%	6%**	7%**
GDP Advance	01.90	10.03	Q	-0.38	14%*	2%	21%**	21%**	23%*	34%**
GDP Preliminary	01.90	10.03	Q	-0.21	16%**	9%	23%**	9%	14%	37%**
GDP Final	01.90	10.03	Q	-0.07	5%	2%	8%	11%	24%*	18%
Trade Balance	11.88	10.03	M	-0.12	13%**	15%**	17%**	9%	18%**	17%
Hausing Starts	11.88	10.03	M	0.13	5%	4%	17%**	13%**	29%**	21%*
Industrial Production	11.88	10.03	M	0.05	5%	6%	-	-	10%*	14%**
NAPM Index	01.90	11.03	M	-0.08	2%	10%	1%	4%	14%**	15%**
Index Leaders Indic.	11.88	10.03	M	0.10	7%	4%	-	-	16%	24%**
New Home Sales	11.88	10.03	M	0.13	7%*	5%	3%	2%	10%*	16%**
Nonfarm Payrolls	11.88	11.03	M	-0.15	19%**	18%**	24%**	32%**	29%**	29%**
Pers. Cons. Expen. / F	11.88	11.93	M	0.18	8%	8%	2%	5%	25%**	34%**
Pers. Cons. Expen. / G	12.93	10.03	M	0.16	9%	5%	6%	11%*	5%	14%
Personal Income / F	11.88	12.93	M	0.18	9%	6%	2%	5%	8%	10%*
Personal Income / G	01.94	10.03	M	0.15	8%	12%	6%	11%*	17%	18%
Producer Price Index	11.88	10.03	M	-0.13	18%*	8%	22%**	17%**	29%**	29%**
Retail Sales	11.88	10.03	M	-0.04	13%*	7%	14%**	27%**	26%**	26%**
Unemployment Rate	11.88	11.03	M	-0.23	19%**	19%**	24%**	33%**	29%**	29%**
Non-Announcement										
Time Interval	08:30	08:45			6%	6%	6%	6%	12%	14%
Time Interval	09:15	09:30			4%	4%	-	-	6%	6%
Time Interval	10:00	10:15			3%	5%	4%	4%	5%	6%
Time Interval	14:15	14:30			2%	2%	1%	1%	7%	6%
Time Interval	15:00	15:15			2%	2%	1%	1%	-	-

1 In 01/1997, the announcement time moved from 10:00 to 8:30 EST.

2 Whenever GDP is released on the same day, durable goods announcement time is moved to 10:00 EST. On 07/1996, it was exceptionally released at 9:00 EST.

3 In 12/1993, the announcement time moved from 10:00 to 8:30 EST.

4 In 01/1994, the announcement time moved from 10:00 to 8:30 EST.

Table 6: Surprise Effect in News Announcements on High Prices

This table shows the estimated coefficients for the following regressions:

$$\Delta p_t^H = \alpha_{k+}\beta_k \Delta p_{t-1,k}^H + \theta_k S_{t,k} + \epsilon_t$$

The dependent variable is the high-to-high price change as the log difference between the highest prices at the announcement day and the day before times 1,000. The explanatory variables are a constant (const), an autoregressive variable (AR) and , $S_{t,k}$ which is the standardised surprise component (Surp.) in the news item k announced on day t. The different k news items are listed in the first column. Three representative assets are considered, namely the Swiss franc to US dollar spot exchange rate, futures contracts on the S&P 500 Index and futures contracts on the US treasury notes (CHF/USD, SP and TY). R-squares statistics for each regression are in percentage. ** (*) indicates that the parameter is significant at least at 1% (5%) probability based on the Newey and West (1987) standard errors.

	CHF/USD				SP				TY			
Announcement	const	AR	Surp.	R2	const	AR	Surp.	R2	const	AR	Surp.	R2
Business Inv.	-0.08	0.13*	-0.17	4.4%	-1.32	0.19*	-0.96	4.4%	-0.90*	0.02	0.34	0.6%
Capacity Util.	-0.29	0.13	0.63	2.8%	-	-	-		-0.03	0.05	-0.64*	4.0%
Construction.	0.12	0.11	-0.83	3.2%	0.95	0.00	-0.96	1.1%	0.54	0.07	-0.30	1.3%
Cons. Conf.	-0.48	-0.04	1.51**	8.0%	0.02	0.11*	0.88	3.3%	0.81**	0.09	-1.23**	14.6%
Credit	0.47	0.00	0.31	0.3%	-0.71	0.03	0.43	0.5%	-	-	-	
C.P.I.	-0.70	0.09	0.56	1.7%	-1.25	0.10	-2.79**	8.8%	-0.07	-0.07	-0.08	0.1%
Durable Goods	-0.32	-0.02	0.90*	3.0%	-0.53	0.07	-0.77	1.7%	0.80*	-0.05	-0.79**	5.6%
Factory Orders	-0.03	0.04	-0.44	0.9%	-0.49	0.11	-0.64	2.4%	0.39	-0.03	-0.77*	3.8%
FOMC target	1.86*	-0.06	0.58	1.7%	2.78	0.08	-0.43	0.9%	-0.28	-0.03	0.54	2.5%
GDP Adv.	0.34	0.10	-1.76	8.5%	2.25	0.01	-0.77	0.5%	2.34**	0.02	0.24	0.4%
GDP Prel.	-0.65	0.23	-3.46	9.5%	-0.68	0.05	1.02	2.5%	0.10	0.20	0.30	7.2%
GDP Final	-1.15	0.03	0.12	0.3%	1.35	-0.05	-2.20	8.1%	0.49	0.00	0.12	0.1%
Trade Balance	0.47	0.01	0.81	1.8%	0.12	0.05	3.16**	8.7%	0.31	0.01	0.00	0.0%
Hausing Starts	-1.65*	0.17*	1.06*	6.3%	0.22	0.05	0.28	0.5%	0.42	-0.03	-0.13	0.3%
Industrial Prod.	-0.13	0.11	0.86	3.4%	-	-	-		-0.23	0.04	-0.28	1.3%
NAPM Index	0.91	0.12	1.58**	8.6%	0.40	0.01	-0.27	0.1%	0.64	0.01	-1.78**	18.6%
Leaders Indic.	0.14	0.06	0.62	1.8%	0.10	0.16*	0.49	4.6%	0.45	0.15*	-0.72*	5.5%
New Home S.	-0.24	0.06	0.56	1.7%	0.46	0.06	-1.19*	3.8%	0.09	0.04	-0.67*	3.3%
Nonfarm Payr.	1.35*	-0.04	1.53**	7.9%	3.58*	-0.07	-1.64	2.5%	1.87**	0.11	-2.29**	27.2%
P.C.E.	1.14	-0.09	0.65	2.2%	-1.36	0.08	-0.86	1.5%	0.93*	0.04	-0.30	0.8%
Personal Inc.	1.09	-0.08	0.42	1.7%	1.89	-0.06	0.33	0.5%	-0.35	0.10	-0.22	2.3%
P.P.I.	-1.28	0.16*	0.36	4.7%	-0.66	0.19*	-1.06	4.2%	1.20**	0.11	-0.63*	4.1%
Retail Sales	-0.60	0.22*	0.02	4.7%	1.61	0.08	-0.23	1.4%	0.19	-0.09	-1.41*	2.1%
Unemployment	1.17*	-0.07	-0.98*	3.7%	3.78*	-0.06	0.67	0.7%	2.55**	0.06	1.28**	8.6%

Table 7: Surprise Effect in News Announcements on Low Prices

This table shows the estimated coefficients for the following regressions:

$$\Delta p_t^L = \alpha_{k+}\beta_k \Delta p_{t-1,k}^L + \theta_k S_{t,k} + \epsilon_t$$

The dependent variable is the low-to-low price change as the log difference between the lowest prices at the announcement day and the day before times 1,000. The explanatory variables are a constant (const), an autoregressive variable (AR) and , $S_{t,k}$ which is the standardised surprise component (Surp.) in the news item k announced on day t. The different k news items are listed in the first column. Three representative assets are considered, namely the Swiss franc to US dollar spot exchange rate, futures contracts on the S&P 500 Index and futures contracts on the US treasury notes (CHF/USD, SP and TY). R-squares statistics for each regression are in percentage. ** (*) indicates that the parameter is significant at least at 1% (5%) probability based on the Newey and West (1987) standard errors.

	CHF/USD				SP				TY			
Announcement	const	AR	Surp.	R2	const	AR	Surp.	R2	const	AR	Surp.	R2
Business Inv.	0.58	0.08	-0.95	2.2%	2.73*	0.21*	-1.28	5.5%	0.02	0.04	0.55	2.3%
Capacity Util.	0.49	0.11	0.09	1.1%	-	-	-		0.24	0.05	-0.71*	4.7%
Construction.	-1.65	-0.08	-0.03	0.7%	0.49	-0.03	-0.55	0.5%	1.80**	0.19*	-0.41	4.1%
Cons. Conf.	0.02	0.04	0.93	2.5%	2.39*	0.21**	0.83	9.8%	0.24	0.03	-1.45**	22.1%
Credit	0.32	0.05	0.57	1.2%	-0.26	0.00	1.20	0.9%	-	-	-	
C.P.I.	-0.75	-0.03	0.22	0.2%	2.61	0.21*	-2.96*	9.7%	-1.55	-0.04	-0.28	0.1%
Durable Goods	-0.66	-0.03	0.67	1.2%	-0.15	-0.04	-1.80	3.0%	0.69	0.14	-1.14**	12.3%
Factory Orders	1.76	0.22*	-0.72	5.0%	-0.70	-0.11	-0.12	2.2%	-0.03	0.04	-0.76**	4.8%
FOMC target	-1.66*	-0.15*	0.23	5.0%	-0.80	-0.09	-2.66*	4.8%	0.47	0.00	-0.25	0.7%
GDP Adv.	-0.82	-0.07	-2.10*	10.0%	2.64	0.14	0.33	2.2%	0.16	0.09	-0.20	0.5%
GDP Prel.	4.07*	0.31*	-0.62	12.6%	0.98	0.13	0.19	2.3%	0.61	0.01	0.67	5.2%
GDP Final	1.83	0.18	0.22	4.7%	0.42	-0.02	-1.47	1.8%	0.70	0.08	0.28	1.4%
Trade Balance	0.71	0.12	1.17*	4.7%	2.30	0.23*	3.03**	10.3%	-0.40	-0.08	-0.11	1.1%
Hausing Starts	1.40	0.14	-0.71	2.9%	-0.77	-0.16	-0.65	3.6%	-0.12	-0.03	-0.18	0.3%
Industrial Prod.	0.29	0.09	0.60	1.5%	-	-	-		0.04	0.04	-0.12	1.3%
NAPM Index	-1.39	-0.07	0.38	0.8%	-0.21	-0.02	0.27	0.2%	1.10*	0.15	-1.36**	13.6%
Leaders Indic.	1.36	0.16*	0.48	4.1%	2.02	0.12	0.38	1.4%	1.13*	0.15*	0.03	3.6%
New Home S.	1.92*	0.17*	0.51	4.8%	1.55	0.06	-0.06	0.3%	0.68	0.07	-0.70*	4.8%
Nonfarm Payr.	0.77	0.09	1.14*	4.4%	1.61	0.20	-2.06	5.0%	-1.44**	0.11	-2.63**	29.7%
P.C.E.	-1.00	-0.01	0.91	1.5%	2.72	0.11	-0.35	1.6%	0.30	0.01	-0.16	0.2%
Personal Inc.	-0.78	0.00	0.01	0.0%	-0.06	-0.13	1.27	4.3%	2.02**	0.24*	-0.40	7.0%
P.P.I.	0.53	0.12	-0.36	1.4%	0.83	0.05	-1.17	0.6%	0.46	0.19*	-0.59	6.4%
Retail Sales	0.18	0.00	1.10*	4.1%	-0.20	-0.12	0.34	2.1%	-2.30	-0.11	-1.56*	2.4%
Unemployment	0.44	0.07	-0.30	0.8%	2.66	0.20	1.32	3.7%	-0.94	0.10	1.25**	7.6%

Table 8: Surprise Effect in News Announcements Across Business Cycles

The left-hand (right-hand) side refers to the regressions in which the dependent variable is the daily high-to-high (low-to-low) price change in futures contracts on treasury notes multiplied by 1,000. The regression equation is as follows:

$$\Delta p_t = \alpha_{k+} \beta_k \Delta p_{t-1} + \beta_k^* R_t \Delta p_{t-1} + \theta_k S_{t,k} + \theta_k^* R_t S_{t,k} + \epsilon_t$$

R_t is the standardised surprise component in the news item k announced at time t. is a recession indicator which is equal one when the US economy is in recession as defined by the NBER business cycle data. R-squares statistics for each regression are in percentage. ** (*) indicates that the parameter is significant at least at 1% (5%) probability based on the Newey and West (1987) standard errors.

	High						**Low**					
Announcement	α	β	β*	θ	θ*	R2	α	β	β*	θ	θ*	R2
Business Inv.	-0.96*	0.01	0.22	0.32	0.65	1.2%	0.00	0.04	-0.03	0.54	0.45	2.3%
Capacity Util.	0.09	0.08	0.04	-0.99**	0.01**	7.9%	0.25	0.05	-0.16	-0.91**	1.76*	6.8%
Construction.	0.51	0.03	0.23	-0.40	0.22	3.0%	1.83**	0.20*	-0.05	-0.58	2.10*	6.3%
Cons. Conf.	0.81*	0.15	-0.03	-1.30**	0.58	14.9%	0.17	0.02	-0.01	-1.35**	-0.98	23.0%
C.P.I.	-0.07	0.00	0.09	-0.08	0.98	0.1%	-1.56	-0.03	-0.15	-0.24	-0.31	0.2%
Durable Goods	0.80*	0.06	-0.08	-0.76**	0.79	5.7%	0.69	0.11	0.29	-1.09**	-0.64	14.1%
Factory Orders	0.41	0.05	-0.18	-0.85*	0.56	4.6%	-0.07	0.04	-0.14	-0.83**	0.46	5.3%
FOMC target	-0.19	0.03	0.07	0.73	0.52	3.2%	0.74	0.00	0.03	0.28	-1.70	7.0%
GDP Adv.	2.43**	0.08	0.91	-0.06	0.05*	8.1%	0.37	0.13	-0.33	-0.43	2.73	3.9%
GDP Prel.	0.14	0.14	-0.35	0.44	0.27	13.6%	0.57	-0.06	0.34	0.84*	-1.90	15.0%
GDP Final	0.51	0.00	0.09	0.11	0.97	0.2%	0.59	0.04	0.23	0.26	0.99	3.2%
Trade Balance	0.31	0.00	0.09	0.06	0.67	0.3%	-0.39	-0.08	-0.03	0.08	-0.98	2.0%
Hausing Starts	0.45	0.01	0.00	-0.20	0.43	0.8%	-0.18	-0.02	-0.15	-0.19	0.66	0.9%
Industrial Prod.	-0.11	0.04	0.13	-0.66*	0.06*	3.9%	0.14	0.05	-0.12	-0.37	0.86	2.7%
NAPM Index	0.65	0.19	0.15	-1.70**	0.55	19.3%	1.06*	0.17	-0.27	-1.28**	-1.27	15.3%
Leaders Indic.	0.48	0.06*	-0.06	-0.87**	0.26	6.4%	1.21*	0.16*	0.00	-0.11	1.05	4.8%
New Home S.	0.09	0.04	0.11	-0.73*	0.49	4.1%	0.70	0.06	0.30	-0.80**	1.62	6.8%
Nonfarm Payr.	1.91**	0.28	-0.08	-2.37**	0.52	27.6%	-1.44*	0.10	0.22	-2.69**	-0.08	30.0%
P.C.E.	0.92*	0.01	-0.06	-0.14	0.29	1.5%	0.21	-0.03	0.24	-0.11	-0.22	1.8%
Personal Inc.	-0.36	0.03	-0.13	-0.21	0.98	2.6%	2.02**	0.25**	-0.09	-0.46	1.29	7.9%
P.P.I.	1.18*	0.07*	-0.33*	-0.59	0.99	6.7%	0.45	0.20*	-0.05	-0.61	0.21	6.5%
Retail Sales	0.21	0.02	-0.05	-1.59*	0.47	2.5%	-2.30	-0.09	-0.16	-1.61*	0.67	2.5%
Unemployment	2.55**	0.09	0.01	1.24**	0.70	8.7%	-0.95	0.11	-0.16	1.28**	-0.52	7.9%

Table 9: Estimates from the VECM models

This table shows the estimates of the following vector autoregressive and cointegrating model:

$$\Delta p_t^H = \left(1p_{t-1}^H - \beta p_{t-1}^L - \mu\right)\alpha_1 + \sum_k \gamma_{1,k}\Delta p_{t-k}^H + \sum_k \lambda_{1,k}\Delta p_{t-k}^L + \epsilon_{1,t}$$

$$\Delta p_t^L = \left(1p_{t-1}^H - \beta p_{t-1}^L - \mu\right)\alpha_2 + \sum_k \gamma_{2,k}\Delta p_{t-k}^H + \sum_k \lambda_{2,k}\Delta p_{t-k}^L + \epsilon_{2,t}$$

where $\Delta p_t^H(\Delta p_t^L)$ is the logarithmic high-to-high (low-to-low) price change between t and t-1, and $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are the residuals for the high (H) and low (L) equation, respectively. Three timeframes are considered: hours, days and months; k is 5, 3 and 1 for the hourly, daily and monthly regressions, respectively. Three representative assets are analysed: the CHF/USD spot exchange rate (CHF/USD), futures on the S&P 500 index (SP) and futures on Treasury notes (TY). * (#) means a probability of the t-statistics at least at 1% (5%) significance level. The last column shows the R-square statistics..

Panel A: Hourly Time Intervals

CHF/USD

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-1.001*	-0.002	H	-0.185*	0.082*	-0.077*	0.026*	0.001	0.012*	0.252*	-0.049*	0.008	-0.018*	-0.006	0.143
		L	0.171*	0.281*	-0.037	0.045*	0.004	0.054*	0.054*	-0.087*	-0.013#	-0.025*	-0.010#	0.171

SP

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-0.983*	-7.478	H	-0.286*	-0.086*	-0.197*	-0.008*	-0.088	0.050#	0.237*	0.071*	0.024	0.076	-0.062	0.167
		L	0.251*	0.412	0.278#	0.273	0.072	-0.049	-0.049#	-0.306*	-0.290*	-0.01	0.051	0.251

TY

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-1.002*	-0.008	H	-0.256*	-0.060*	-0.074*	-0.054*	-0.044*	-0.015*	0.199*	0.045*	0.068*	0.062*	0.027*	0.091
		L	0.197*	0.228*	0.109*	0.109*	0.100*	-0.078*	-0.078*	-0.136*	-0.094*	-0.083*	-0.055*	0.197

Panel B: Daily Time Intervals

CHF/USD

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-0.975*	-0.054	H	-0.926*	0.544*	0.211*	0.154*			-0.246*	-0.275*	-0.154*			0.326
		L	0.367*	0.134#	0.004	-0.034			0.135#	0.003	0.017			0.202

SP

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-1.020*	4.204	H	-0.037	-0.264*	-0.271*	-0.099*			0.407*	0.136*	0.113*			0.112
		L	0.328*	0.298*	-0.005	0.001			0.012	-0.098	0.015			0.118

TY

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-1.004*	-0.112	H	-0.341*	-0.103*	-0.147*	-0.106*			0.275*	0.103*	0.066*			0.131
		L	0.261*	0.146*	0.019	0.021			0.03	-0.04	-0.049#			0.062

Panel C: Monthly Time Intervals

CHF/USD

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-1.051*	0.001	H	-0.385#	-0.044					0.321#					0.238
		L	0.727*	0.038					0.380*					0.171

SP

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-0.939*	-45.27	H	-0.383*	0.175					0.008					0.14
		L	0.843#	0.046					0.253					0.174

TY

β	μ		α	γ1	γ2	γ3	γ4	γ5	λ1	λ2	λ3	λ4	λ5	R-2
-1.014*	-1.517	H	-0.568*	-0.03					0.480#					0.515
		L	0.222	-0.044					0.298*					0.046

Table 10: Out-of-the-sample forecasts

This table shows the out-of-sample forecasts based the VAR-EC model between high and low prices. These predictions are compared with a naïve forecasting strategy using the most recent historical data. Three timeframes are considered: hours, days and months. The length k of lag order in the VAR is 5, 3 and 1 for the hourly, daily and monthly regressions, respectively. Three representative assets are analysed: the CHF/USD spot exchange rate (CHF/USD), futures on the S&P 500 index (SP) and Treasury notes (TY). On the left-hand side, this table shows the hit ratio to assess how many times forecasts correctly predict the direction of high-to-high (HH) and low-to-low (LL) price changes. The hit ratio called "close-within-range" and "mid-price-within-range" calculate how many times the last price and the mid-price respectively lie within the forecast range. The mid-price is the sum of the first and last prices divided by two. We use the Diebold-Mariano method to test the null hypothesis of no difference in the accuracy between the naïve and VECM forecasts. On the left-hand side, this table reports the regression results between the actual range (dependent variable) and forecast range and a constant (explanatory variables). For the naïve strategy, the previous actual range replaces the forecast range. The last three columns show the regression R-squares, the Chi-square values of the Wald tests for the null hypothesis that beta is different from one, and the root-mean-square error (RMSE). ** (*) means a probability rejection of the null hypothesis at least at 1% (5%) of significance level.

		HH	LL	Close within Range	Mid-Price within Range	Alpha	Beta	R2	Wald test β=1	RMSE (%)
CHF/USD	Day	0.623**	0.616**	0.586*	0.771**	0.000	0.963	0.220	0.555	0.22
	Naïve	0.498	0.476	0.536	0.697	0.003	0.253	0.064	541.6**	0.30
	Month	0.708**	0.596**	0.542*	0.791**	-0.003	1.087	0.240	0.254	1.34
	Naïve	0.563	0.592	0.479	0.634	0.059	-0.195	0.037	103.7**	2.12
SP	Day	0.611**	0.585*	0.701*	0.726**	0.000	0.987	0.494	0.104	0.26
	Naïve	0.518	0.533	0.675	0.585	0.002	0.502	0.252	178.4**	0.35
	Month	0.740*	0.677*	0.530**	0.813**	0.003	0.980	0.495	0.052	2.98
	Naïve	0.684	0.600	0.442	0.642	0.055	0.338	0.114	28.8**	4.26
TY	Day	0.604**	0.582**	0.491*	0.628**	0.000	0.907	0.130	3.265	0.11
	Naïve	0.487	0.498	0.471	0.550	0.001	0.192	0.036	1075**	0.14
	Month	0.696**	0.609*	0.583**	0.739**	0.002	0.982	0.101	0.055	1.41
	Naïve	0.535	0.570	0.474	0.623	0.025	0.082	0.006	95.2**	1.98

Figure 1A: CHF/USD exchange rates

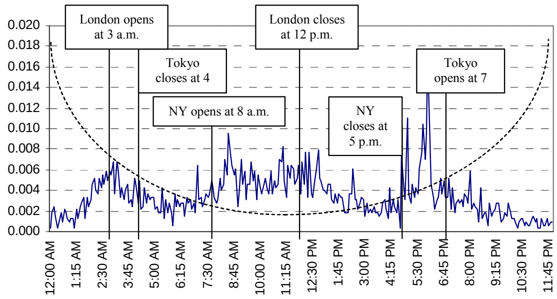

Figure 1B: SP 500 index futures

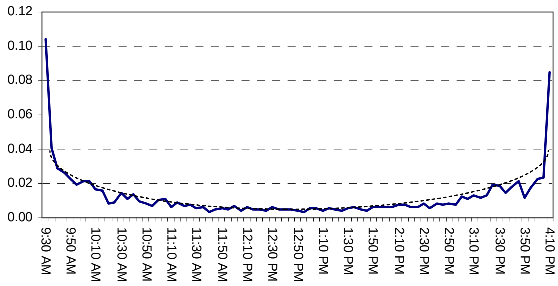

Figure 1C: TY futures

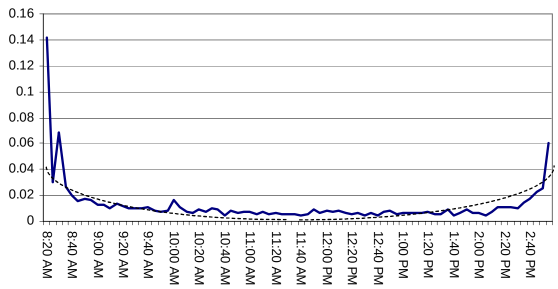

Figure 1: These three figures show the relative frequency of the intraday occurrence of the highest traded price for the CHF/USD spot exchange rate (Figure 1A), the S&P 500 index futures during open-outcry trading hours (Figure 1B) and the treasury yields futures (Figure 1C). The dotted grey lines plot the intraday location of extreme prices implied by the arc-sine law. The time of the trading day is in Eastern Time (ET).

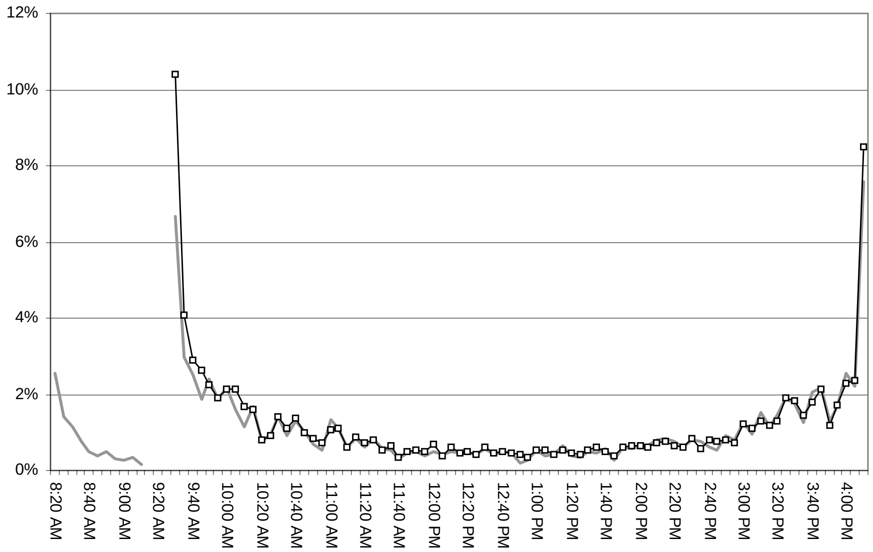

Figure 2: This figure shows the relative frequency of the intraday occurrence of the highest traded price for the S&P 500 Index futures. Two trading times are considered: first, the trading hours during the open-outcry trading hours (black line marked by white squares); second, the open-outcry trading hours extended by the last hour of the Globex trading (from 8:20 a.m. to 9:15 a.m.) (grey line). The sample period for the former (latter) curve is from 7 November 1988 to the end of May 2003 (from 9 September 1993 to end of May 2003). The time of the trading day is in Eastern Time (ET).

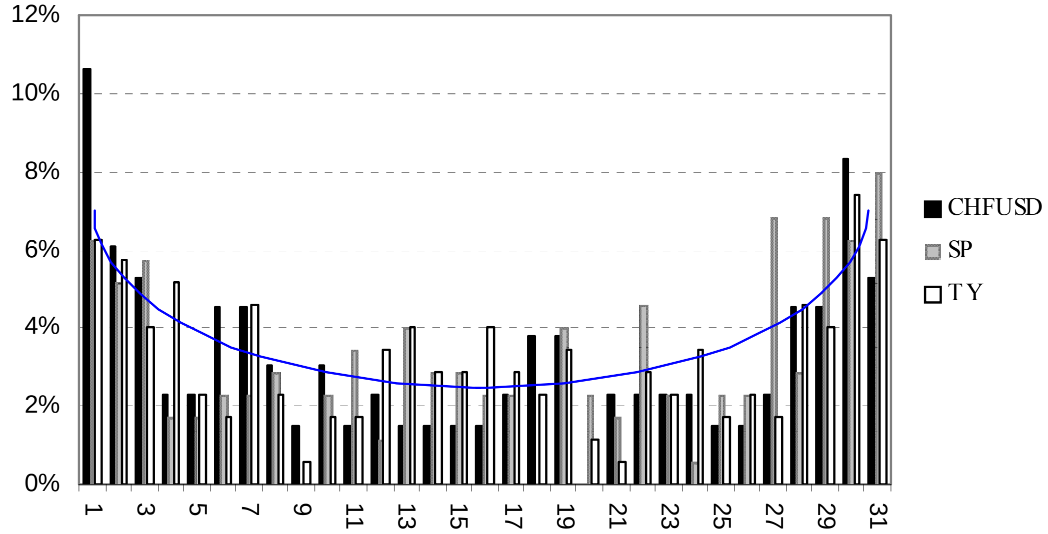

Figure 3: This figure shows the relative frequency of the intra-month occurrence of the highest prices for the CHF/USD spot exchange rate (black bars), the S&P 500 index futures (grey bars) and the treasury yields futures (white bars). The black line plots the intra-month location of extreme prices implied by the arc-sine law. The horizontal axis represents the day of the month.

Figure 4.1.: Response to a Shock from the Daily Highest Price

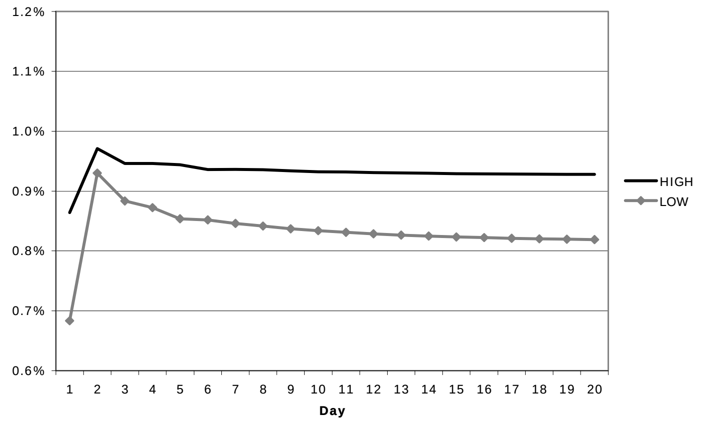

Figure 4.2.: Response to a Shock from the Daily Lowest Price

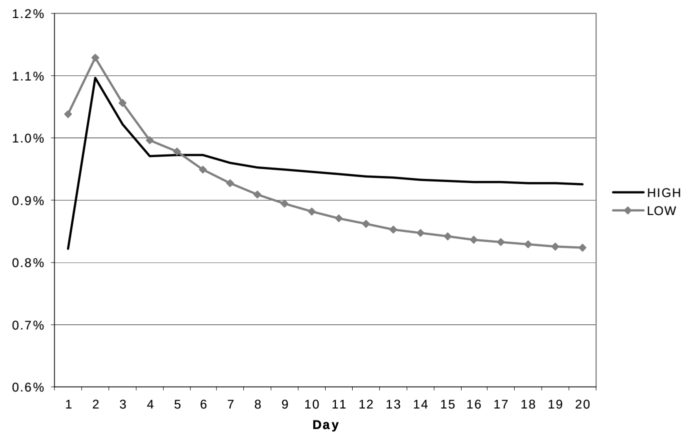

Figure 4: Generalized Impulse-Response Analysis for Daily Shocks in the S&P 500 Index Futures Market

Figure 5.1.: Response to a Shock from the Monthly Highest Price

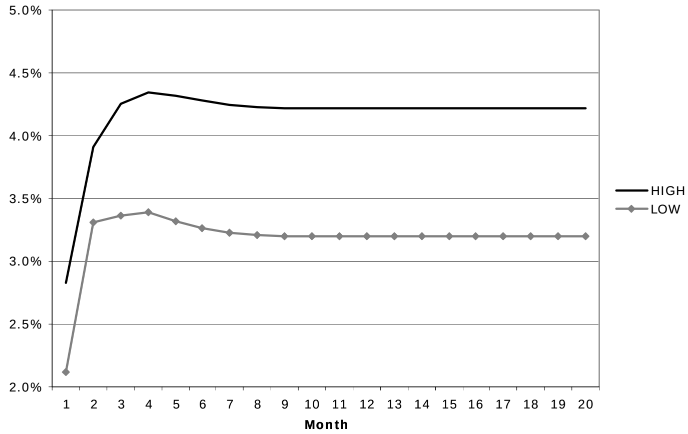

Figure 5.2.: Response to a Shock from the Monthly Lowest Price

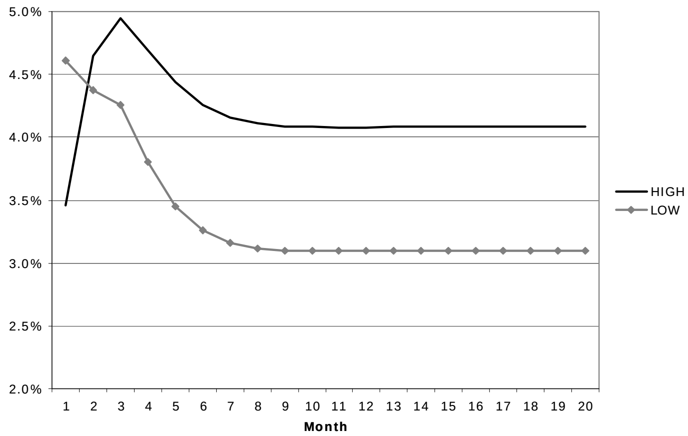

Figure 5: Generalized Impulse-Response Analysis for Monthly Shocks in the S&P 500 Index Futures