Information Content and Predictability of Extreme Prices in Financial Markets*

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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). The Geometric Brownian motion properties hold only partially for extreme prices. Macroeconomic news announcements and surprises are major determinants of extremes. The econometric reasons justifying a vector autoregression with error correction are provided by auto-correlation, cross-correlation and cointegration between highs and lows. Evidence on the predictability of extreme prices is provided.
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 and efficient market hypothesis? Do these stylised facts hold across asset classes and time horizons? Are extremes triggered by the release of public information? Can we identify which news bulletins lead to 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.

There are four respects in which high and low prices can be informative. First, they inform people's thinking. Kahneman and Tversky (1979) show that when forming estimates, people start with an initial arbitrary value, and then adjust it in a slow process. In more general terms, behavioural finance studies have shown that agents' behaviour generally depends on reference levels. In these and other forms of mental accounting and framing, previous highs and lows typically represent the reference values for future resistance levels.[1] Second, as highlighted in the literature on market microstructure, high and low prices convey information about liquidity provision and the price discovery process.[2] Third, high and low prices actually shape the decisions of many kinds of market participants, e.g. technical analysts.[3] More generally, any investor using path-dependent strategy typically tracks the past history of extreme prices. Thus, limit prices in pending stop-loss orders often match the most extreme prices in a previous representative period. 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 have been many studies on the range[4]. This literature shows that the range-based estimation of volatility is highly statistically efficient and robust with respect to many microstructure frictions.

This research has three main objectives: First, to perform an explorative

[1] See, e.g., Curcio and Goodhart (1992), DeGrauwe and Decupere (1992) and Osler (2000)

[2] 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.

[3] 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)), and that support and resistance levels coincide with liquidity clustering (Kavajecz and Odders-White (2004)). The large use of technical analysis especially at short time horizons (intraday to one week) is documented in, e.g., Allen and Taylor (1990).

[4] 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 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).

analysis into the information content of extreme prices. We examine the main statistical characteristics of high and low prices across different time granularities (hourly, daily and monthly) and different asset classes. We compare the empirical facts on extreme prices with the analytical properties of a geometric Brownian motion. 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 behaviour over representative periods of recession and expansion, and to infer stylised facts that hold for different categories of financial assets.

Since the real patterns of extreme prices differ from the pure properties of a stochastic process, the second objective is to investigate one of the possible reasons for this difference. We focus our analysis on public information announcements. On the one hand, we analyse whether and to what extent the occurrence of extremes is more likely after the announcement of major prescheduled US macroeconomic news bulletins. On the other hand, we examine how the surprise, or unexpected component, in the news announcement affects 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 ("VEC") 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 prices 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. Contrary to 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 in 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, as predicted by the arc-sine law, 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 microstructural aspects. Finally, the joint behaviour of high and low prices is considered. Two main stylised facts emerge: the range is also serially autocorrelated; high and low prices deviate in the short run but steadily converge in the long run. In other words, high and low prices exhibit a cointegrated pattern.

Second, we investigate one possible reason for the occurrence of extreme prices: public information releases. We find that extremes in the bond, currency and equity markets are significantly linked to US macroeconomic news releases. 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.

Finally, 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 simple, this econometric specification represents a straightforward and efficient method of capturing 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 at a fixed point in time (say, at closing) are almost unpredictable. This paper shows that unpredictability does not hold for extreme prices and that the next extreme prices can be forecast simply by using past high and low prices that are readily available.

The present paper is structured as follows. Section 2 introduces some analytical aspects of the stochastic behaviour of high and low prices. Section 3 shows the main empirical findings of the explorative analysis. Section 4 presents the econometric model. Section 5 analyses whether extremes are associated with macroeconomic news releases. Section 6 presents the forecasting analysis. Section 7 concludes the paper.

2 Some analytical aspects of high and low prices

In this first part of our research, we surveyed some simple analytical aspects of the stochastic behaviour of high and low prices. Using the standard properties of a geometric Brownian motion, we formed a number of hypotheses on the stochastic process of high and low prices. These hypotheses were tested in a later part of our project.

We first focused on the position in time of the high and low prices. Feller

(1968) shows that one of the surprising features of chance fluctuations in the results from tossing a coin finds its expression in the arc-sine law. To illustrate this, 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 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 should observe a well-defined and symmetrical U-shape. This argument brings us to the first hypothesis for testing:

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 that 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 in 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 time of occurrence of $p^H_{k,t}$ depends on $p^H_{k-1,t}$. This definition of high-to-high price change implies overlapping increments in 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 $p_{k,t}^{H}$ becomes

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

That is, $p_{k,t}^{H}$ is independent of S_{k-1}. The Williams theorem suggests another method for representing 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.

A more general way to understand why first-to-high, first-to-low and the range should be independent identically-distributed random variables is to evoke the Lévy theorem of Brownian local time. To obtain an intuitive view of the relation between Brownian motion and the 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 though the cointegrated scheme may 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, taking the GMT time to define the daily clock time. When we consider intraday and monthly timeframes, "first price" denotes the first traded price in 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 lasted 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 are released 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 lasted 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. for the Globex trading platform. This prevents us from analysing the news impact for Capacity Utilization and Industrial Production bulletins that are released at 9:15 a.m. The data contain the time stamp, to the nearest minute, and the transaction prices of all trades for 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 mean of the representative ask and bid quotes). Although indicative quotes have their shortcomings, a 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), p. 126).

Table 1 reports the number of observations for each asset. It also shows some descriptive statistics relating to 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 for 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. Of these assets, price changes in 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 time 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 appear 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, during the open-outcry trading hours, extreme S&P futures prices occur much more frequently around the beginning and end of the trading day than we would have expected from the arc-sine law (see dotted lines). By extending the CME Globex trading time by one hour (from 8:15 to 9:15 a.m.), 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[5] 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 depicts the intraday location of highs and lows on the foreign exchange market and clearly shows that the occurrence of extremes depends on many other aspects. In particular, it seems that the timing of extremes is determined by trading hours in the world's three major regions, 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.).[6] It can be seen that the probability peaks for extreme prices correspond to the opening and closing 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. Another argument stresses information asymmetry among market participants. As suggested by Admati and Pfleiderer (1988), when adverse selection risk is high, liquidity traders are better off clustering their trading over time. The occurrence of extreme prices may coincide with those clustering moments.

The intraday pattern of treasury yield futures at the CBOT also deserves close consideration. We note that the probability of highs and lows increases at 8:30 and 10 a.m., when the major macroeconomic news bulletins are released.[7] 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 (2006)), U.S. bonds tend to react more than US stocks to macroeconomic news releases. Thus, these results suggest that the location time of extreme prices depends critically 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 timing of intra-monthly extreme prices fits better to the arc-sine law. Figure 5 shows that the occurrence of high and low prices is more probable at

[5] E.g. Brock and Kleidon (1992), Chung, Van Ness and Van Ness (1999), Lehmann and Modest (1994) and Olsen et al. (1997), only to mention a few.

[6] There are many other papers showing how trading activity across different geographic regions determines intraday seasonalities on forex markets; see e.g. the recent contribution by Ito and Hashimoto (2005).

[7] At 8:30 a.m.: 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. At 10 a.m.: New Home Sales, Factory Orders, Construction Spending, Consumer Confidence Index, and ISM Index.

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

3.3 Autocorrelation

The second hypothesis set out above is that high-to-high (low-to-low) price changes are time-dependent and therefore we would 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 that no autocorrelation is expected. Table 2 shows that *both* high-to-high and first-to-high price change definitions follow a significantly autocorrelated process.[8] This autocorrelated pattern persists over several lags. Since the autocorrelation coefficients die off geometrically with increasing lags, the price change series involving extreme prices appear to conform to 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.

There are many reasons for autocorrelated patterns. Reversal patterns may stem from profit-taking or over-reaction behaviour. Negative autocorrelation over short timeframes may also be due to microstructural issues such as bid-ask spread bounces, discrete or rounded prices. On the other hand, return continuation in the same direction may be driven by a sustained process of price adjustment to new public information, information leakages, herding behaviour or more specific phenomena over time, such as the emergence of price bubbles or temporary trends. In table 2, the sign of the autocorrelation process is generally positive. This supports the price continuation hypothesis.

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

We also conducted an analysis aimed at determining whether any periodic fluctuations or time seasonality affect our results. To do this, we used different methods and detected seasonalities only for intraday price changes. Three main methods were used: first, filtering out seasonalities with averages for the same

[8] For ease 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.

time of the 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 based on Andersen and Bollerslev (1997 and 1998). Our results (not tabulated)[9] suggest that the documented autocorrelated pattern in high-to-high, first-to-high, low-to-low, first-to-low and range remains, even after adjusting for intraday seasonalities.

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 for 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)). Along 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 presented 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 may be due to the longer length of the open-to-close period. Put differently, the open-to-close period embraces a 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 returns, even for daily and monthly time intervals. It is also noticeable that the effect of past open-to-low returns on open-to-high returns appears stronger. This suggests that price level adjustments from below may have a greater effect.

The stickiness of high and low prices may be due to the existence of resistance levels and the use of rounded and reference numbers. The nature of rounded or reference numbers can be varied: e.g. mental accounting, price discreteness, reference prices in related markets such as strike prices for 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 recent high and low prices. Thus, past market turning points tend to determine the next trading range. High and low

[9] This additional analysis is available upon request.

prices therefore represent future support and resistance levels. Finally, these kinds of persistence may be due to the ways in which information is released and the ways in which agents process information to form prices. Hung and Plott (2001) show how information cascades can engender "herding" behaviour and thus a prolonged process of price adjustment. Furthermore, the analysis of certain information items may objectively be time-consuming, undergoing a lengthy process before being completely incorporated into asset prices.

3.4 Cointegration

Hypothesis 5 states that high and low prices exhibit cointegrated behaviour. Since non-stationarity is a pre-condition for 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 a significance level of 1% in all cases but one (for CHF/USD monthly data the rejection is at a significance level of 5%). 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 Modelling high and low asset prices

4.1 Econometric framework

In the explorative part above, we found that high and low prices are characterised by these three main properties: serial correlation, cross-correlation and cointegration. Therefore, the natural econometric framework for modelling extreme prices is an vector autoregressive model with error correction (hereafter VEC).

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) (non-stationary) representation at price levels where $\mathbf{p}_t = \left(p_t^H, p_t^L\right)'$:

$$\mathbf{p}_t = c + \sum_{k=1}^{K} \mathbf{A}_k \mathbf{p}_{t-k} + \mathbf{e}_t \tag{7}$$

$$\mathbf{e}_t = (e_{1,t}, e_{2,t})' \sim iid\,(0, \sum) \tag{8}$$

$$\sum = \begin{bmatrix} \sigma_1^2 & \sigma_{2,1} \\ \sigma_{1,2} & \sigma_2^2 \end{bmatrix} \tag{9}$$

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

$$\Delta\mathbf{p}_t = \alpha\left(\beta'\mathbf{p}_{t-1} - \mu\right) + \sum_{k=1}^{K-1} \Gamma_k \Delta\mathbf{p}_{t-k} + \mathbf{e}_t \tag{10}$$

Where

$$\alpha\beta' = -\mathbf{A}\,(1) = -\left(\mathbf{I}_2 - \sum_{k=1}^{K} \mathbf{A}_k\right) \tag{11}$$

$$\mathbf{\Gamma}_k = \sum_{j=k+1}^{K} \mathbf{A}_j \tag{12}$$

$$\mu = E\left(\beta'\mathbf{p}_{t-1}\right) \tag{13}$$

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 how quickly each price is expected to eliminate 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 taking the form of 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:

$$\Delta p_t^H = \left(1 p_{t-1}^H - \beta p_{t-1}^L - \mu\right) \alpha_1 + \sum_k \gamma_{1,k} \Delta p_{t-k}^H + \sum_k \lambda_{1,k} \Delta p_{t-k}^L + \epsilon_{1,t} \quad (14)$$

$$\Delta p_t^L = \left(1 p_{t-1}^H - \beta p_{t-1}^L - \mu\right) \alpha_2 + \sum_k \gamma_{2,k} \Delta p_{t-k}^H + \sum_k \lambda_{2,k} \Delta p_{t-k}^L + \epsilon_{2,t} \quad (15)$$

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. the influential role of information announcements, see below). 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 objectives of this paper.

4.2 Empirical analysis

We conducted 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) indicated that 1, 3 and 5 lags were the opportune lengths for monthly, daily and hourly implementation of the VAR model, respectively.

Table 5 shows the results of our estimation of the VEC models over the entire sample periods. To estimate the VEC in this paper, we used the common cointegration methodology based on the maximum likelihood procedure proposed by Johansen (1988). The residual test showed serially uncorrelated but non-normal residuals for daily regressions. For the monthly regressions, residuals were 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 noted that the coefficients of determination (R squares) were fairly high for all time granularities and assets. Intraday estimations provided the highest R-squares (from 14 to 24%) and monthly regressions the smallest ones (5-20%). The S&P futures index showed the best fit. Looking at the high and low regression equations separately, we observed that the higher R squares were obtained for the low regression equation only for the hourly timeframe; for longer timeframes, the high regression equation had higher coefficients of determination. High R squares went hand in hand with the t statistics for the autoregressive coefficients in the VARs; therefore, higher R squares normally corresponded to a longer dependence on past data. This raised the question of whether the asymmetries between high and low prices could be related to leverage effects and short-sale constraints.

We observed that, as expected, all the estimated βs in the normalised cointegration equation were very significant and very close to one. This result bore out the cointegration hypothesis. In principle, it also allowed us to impose the restriction $\beta = 1$. The VEC implementations restricted in this way provided estimates that were slightly more significant (in particular, a larger number of estimated coefficients significantly different from zero, and higher R squares). However, we have 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 allowed analysis of the impulse-response function. We used the generalised impulses proposed by Pesaran and Shin (1998) to construct an orthogonal set of innovations that did not depend on the VAR ordering. The impulse-response function showed how high and low prices reacted to a typical shock (amounting to one standard deviation) emanating from high and low prices. Figures 4 and 5 show the results of impulse-response analysis for daily and monthly shocks in the S&P 500 index future market. In general, the following patterns can be observed: 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-price 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 (say, 10 periods ahead) on high-price levels for S&P index futures. In the long run, however, shocks have a greater effect on low-price levels in the case of 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 into an immediate reaction and a successive response. The immediate reaction comprises a large impact in the first period, continuing weakely throughout the subsequent one or two periods. In the subsequent reaction, the impact reverts in periods 3-6, and then converges towards its long-run level. 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 bid-ask spread enlargement or to a temporary short-term overreaction.

5 Macroeconomic news announcements

The exploratory part of this study revealed some discrepancy between the statistical properties implied by a geometric Brownian motion and the actual patterns of extremes. We therefore attempted to find economic explanations for this discrepancy. There are many possible reasons for the occurrence of extreme prices. Here we limited our analysis to just one possible driver: macroeconomic news announcements. In particular, we analysed (1) whether the occurrence of the high and low price of the day was related to the time when major US economic news is released, and (2) whether the surprise, or unexpected component, of the news announcement impacted on extreme prices. The former question focused on the time of the news announcement (hereafter we will refer to "announcement effect"). The latter issue referred to its information content ("news effect").

We obtained announcement data from Informa Global Markets (Europe) Ltd.[10] For each different macroeconomic announcement, we obtained a time series of the realised values as well as market forecasts based on survey expectations. For most news items, the news data were available for the sample period for which we have access to high frequency data, namely from May 1988 to May 2003. Table 6 shows a list of the news bulletins, the time period (in months) during which this particular bulletin was released, the frequency of releases (monthly, each six-week, or quarterly) and time of day of the announcement dates.

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

[10] In previous studies this data source is denoted the International Money Market Service (MMS). Recent papers using this dataset include Andersen et al. (2003 and 2004), Balduzzi et al. (2001), and Christiansen and Ranaldo (2006). The previous literature shows that announcement days are spread out almost evenly over the different days of the week.

$$S_{i,t} = \frac{A_{i,t} - E_{i,t}}{\sigma_i} \quad (16)$$

where $A_{i,t}$ ($E_{i,t}$) is the realised (expected) value for announcement i at time t. σ_i is the standard deviation of the announcement surprise ($A_{i,t} - E_{i,t}$) across the entire sample. The frequency of daily extremes conditional on the news announcements was compared with non-announcement probability for the same time of day. The length and composition of non-announcement samples was consistent with the announcement data.[11]

5.1 Announcement Effect

All these news bulletins are pre-scheduled. Thus, we were able simply to calculate the frequency of daily extreme prices. An alternative method was to extend our VEC benchmark model (14-15). By taking the compact form, it became:

$$\boldsymbol{\Delta}\mathbf{p}_t = \boldsymbol{\alpha}\left(\boldsymbol{\beta}'\mathbf{p}_{t-1} - \boldsymbol{\mu}\right) + \sum_{k=1}^{K-1} \Gamma_k \boldsymbol{\Delta}\mathbf{p}_{t-k} + \Psi\mathbf{d}_t + \mathbf{e}_t \quad (17)$$

The new component with respect to the general model in (14-15) was the presence of exogenous variables. These were represented by Ψ which was a $2xk$ matrix of parameters and $\mathbf{d}_t$ which was a $2xk$ matrix containing k dummy variables that individually equalled one if the news item k is announced at time t, and zero otherwise. k was equal to 25, 24 and 23 for the CHF/USD spot exchange rates, treasury notes and S&P futures, respectively.

Thus, we had two methods of analysing the announcement effects, namely the frequency and VEC approaches. Both methods essentially provided consistent indications. First, we present the results based on the frequency method (in table 6). We consider that a news announcement is responsible 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 extended to take in the last trading hour at the Globex (for equity futures) and from 8 a.m. to 5 p.m. on the currency market. Currencies are traded round-the-clock. We decided to limit our comparisons to US working time (i.e. from 8 a.m. to 5 p.m.) rather than over 24 hours, since this better captures the US currency market reaction to US news bulletins. We also considered using other time intervals[12] to assess the market reaction. However, previous literature has

[11] 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.

[12] In particular, we considered 15, 30, 45 and 60-minute intervals. We also analysed how

established that a 15-minute period encompasses the typical market response (see, e.g. Andersen et al. (2003, 2004), Balduzzi et al. (2001)). Table 6 reports announcement effects for two different periods to assess any possible difference. A similar attention was given in the VEC analysis.

The following picture clearly emerges from Table 6. Various pre-schedule news announcements significantly increase the incidence of extreme prices (at least at a significance level of 5%). Futures on 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 coincide with 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 the Consumer Price Index. Unemployment Rate and Nonfarm Payrolls releases trigger 56–58% of price extremes in S&P futures and 37–38% of the most extreme 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 lead to more than 41% of the extremes in S&P futures. These findings on the high sensitivity of the equity market to news announcements contrast with the previous literature (e.g. Andersen et al. (2004), Christiansen and Ranaldo (2006)), indicating that macroeconomic news announcements have a weaker impact on equity markets in terms of price and volatility.

The VEC method has the advantage of capturing simultaneous interactions between announcement effects and high and low prices. The results from the VEC regressions are shown in table 7. Notice that, for the sake of presentation, only the estimates for the news (exogenous) variables are presented. Other estimates remained unchanged with respect to the standard model (see table 5). The VEC method suggests that the same set of new bulletins outlined above have a major impact, namely CPI, GDP Advance, Trade balance, Nonfarm payroll, PPI, Retail Sales and Unemployment Rates. However, the impact seems to be less pervasive across markets. Specifically, in many circumstances it is significant only for treasury notes. Interestingly, news announcements seem to

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 period of comparison to determine the extreme for the day. The results are largely consistent with those presented in this paper.

impact rather asymmetrically with respect to high and low prices. Low prices appear more sensitive to news releases for treasury yields and S&P futures. By contrast, high prices react more strongly to news released in the currency market. This result is obtained irrespective of which method is used. See the number of significant coefficients in Table 6 and 7, and the average coefficient estimates in table 7.

5.2 News effect

The information content of a news announcement rather than its release time may affect the formation of extreme prices. To observe this, we analysed whether the surprise (or unexpected) value of announcement k released on day t had an impact on the extreme price for that day. More specifically, the VEC benchmark model (14-15) became:

$$\mathbf{\Delta p}_t = \boldsymbol{\alpha} \left(\boldsymbol{\beta}' \mathbf{p}_{t-1} - \boldsymbol{\mu} \right) + \sum_{k=1}^{K-1} \Gamma_k \mathbf{\Delta p}_{t-k} + \Omega \mathbf{S}_{t,i} + \mathbf{e}_t \tag{18}$$

Here the new elements were exogenous variables represented by $\mathbf{S}_{t,i}$ which is a $2x1$ matrix of the standardised surprise component in the news bulletin i released at time t. On non-announcement days, the surprise component is set to be zero. The remaining terminology is as before.

Table 8 shows the main findings for high and low prices respectively. Again, only the estimated coefficients of the news surprise variables are presented. 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 currency markets appear as the most and least reactive ones. In 6 of the 23 (24) bulletins, news surprises significantly contributed to the formation of the high price of treasury notes futures (CHF/USD spot rates). Again, low prices in bond and equity futures react more strongly to news surprises. Thus, low prices for treasury notes and equities appear to be triggered not only by announcement effects but also by the unanticipated components in the news bulletins (see the number of significant estimates and the average coefficients in table 8).

Again, Nonfarm Payrolls and Unemployment Rates[13] are among the most

[13] Notice that the signs of the surprise component in Unemployment Rate announcements were inverted. We signed a negative (positive) surprise on Unemployment Rates with a positive (negative) sign. This is because a lower-than-expected Unemployment rate is normally considered good news and the other way round. This explains why the estimated coefficients related to the Unemployment Rate surprise in table 8 are positive whereas they are negative in table 2-4 in Andersen et al. (2003, pp. 51-55).

influential bulletins. However, Retail Sales, Durable Goods, ISM[14] and Consumer Confidence also have an impact, especially on bond futures. 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[15]), the currency reaction is consistent with a variety of models of exchange rate determination, central banks' reaction functions 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 the nominal risk-free interest rate. Thus, inflationary and real shocks should decrease bond prices. Empirical support for this view is provided by various authors, including Balduzzi, Elton and Green (2001). 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 in the case of 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.

One pertinent question is whether macroeconomic announcements impact differently across business cycles.[16] After all, market participants may attach different meanings to or make different interpretations for the same news item in different economic regimes. This speaks in favour of conditioning the news impact analysis to economic regimes. We performed this analysis, extending the econometric method for the announcement effect (17) and surprise effect (18) in order to capture any possible state-dependent reaction of extremes.[17] The preliminary results (not displayed) show that the news impact on high and low prices is essentially similar across business cycles.

[14] ISM stands for Institute for Supply Management; it was called the National Association of Purchasing Managers (NAPM) until August 2002.

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

[16] This question has widely been examined. Among the most recent literature, the following is a selection of studies that prompted the inclusion of this additional analysis: Andersen et al. (2004), Boyd, Hu and Jagannathan (2005) and Christiansen and Ranaldo (2006).

[17] More specifically, we used a recession indicator which is equal to one when the US economy is in recession, as defined by the NBER business cycle data.

6 Prediction of extremes

The VEC model presented above was used to calculate out-of-the-sample forecasts. The forecasting analysis was performed on a daily and monthly basis.[18] We compared the forecasting ability of the VEC model with a VEC model specification augmented for the announcement effect (in the spirit of regression 17) and a naive prediction strategy. We start by describing the standard VEC forecasting methodology. The daily and monthly regressions were based on 250 and 60 observations, respectively. This means that we used one year and five years of the past observations to estimate the regression coefficients to be used for the following predictions over daily and monthly periods, respectively. Other estimation periods were also tested. These periods represented a fair compromise, guaranteeing reasonable stability and precision. Each forecast was obtained using these observation numbers. This means that we adopted a “rolling-ahead” procedure: once we had estimated a regression, we calculated the prediction for the next high and low prices and then moved one period ahead by dropping the first observation of the previous estimation period. We obtained 3,000 out-of-the-daily-sample forecasts. For the monthly predictions, we had 72, 96 and 115 out-of-the-sample forecasts for CHF/USD exchange rates, S&P index futures and treasury yield futures, respectively.

To provide a benchmark to the VEC forecasts, we defined a naive forecasting strategy based on past data. The naive forecasting procedure simply consisted of using the earliest high and low prices. For example, the naive high-to-high forecast on a daily basis implied that the price direction from yesterday’s to today’s high determined the price direction from today’s to tomorrow’s high. By the same token, one day’s range represented the naive prediction for the next day’s range. We use the Diebold and Mariano (1995) method to test the null hypothesis of no difference in the accuracy between the naive and VEC forecasts. The test for superior predictive ability proposed by Hansen (2005), which permits to compare more than two forecasted series, provided the same results.[19]

We attempted to enhance the standard VEC forecasting model by means of the information content of news announcements. In table 9, we call this method "VEC-news model". To run this model, a longer in-sample period is needed. By construction, the estimation procedure of VEC-news specification

[18] 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.

[19] This additional analysis is available upon request.

required long time series for the exogenous variables, i.e. the announcement indicators. For the results in table 9, we used 2,500 in-sample observations. Other sample periods were considered. We decided to present a uniform starting time for the out-of-sample VEC-news predictions that virtually coincided with the beginning of the bear market and the partially overlapping recession phase.[20] This occurred in September 2000.

Table 9 shows the results of some simple tests conducted in order to assess how the predictions derived from the different models fitted with real data. We employed two main methods: hit ratios and regressions. Hit ratios evaluate the extent to which forecasts are able to predict actual future data. Table 9 presents four hit ratios. Two of them measure how many times the 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 used 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 was 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 considered other price definitions and points of time as well as the Pesaran-Timmermann (1992) method to test the correct prediction of the direction of changes.[21]

The broad picture revealed by table 9 is that the VEC model shows significant ability in predicting extreme prices over daily and monthly timeframes. High-to-high and low-to-low returns suggest that VEC predictions capture the correct direction of future price movements. Hit ratios for the predicted direction of extreme prices lie between 57% and 74%, which is much higher than the analogous hit ratio performance for predicting closing prices (e.g. Pesaran and Timmermann (1995)). The close-within-range and mid-price-within-range ratios show that we can significantly enhance the prediction precision of future prices using VEC forecasts.[22] It is worth noting that the simple VEC model seems to outperform the VEC-news model despite the additional information

[20] More precisely, the NBER definition of this recession phase goes from the beginning of March to the end of October 2001.

[21] For instance, we considered the midday price (which corresponded 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.

[22] 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).

content about the news announcement times. This is probably due to the difference in in-sample period lengths. The standard VEC is based on a shorter estimation period (i.e. less than one year). This time period is apparently more informative on the forthcoming extreme price patterns. By comparison, the VEC-news model had to be implemented over much longer estimation periods (typically more than 8 years) and it outwardly failed to capture the leading trends.

The second method for testing how good these forecasts were, was to regress the actual range on the forecast one.[23] We performed a simple linear least-square regression where the dependent variable was the actual range and the explanatory variables were the forecast range and a constant. We also accounted for heteroskedasticity and residual autocorrelation by using the Newey-West (1987) adjustments for the standard errors and covariance. Table 9 shows that the estimated coefficients relating the VEC forecast and the actual ranges (called beta) were always extremely significant (at a significance level of 1%) and close to one, whereas the constant was negligible. More important, the Chi-square values related to Wald test for the null hypothesis that beta was equal to one could never be rejected. The R squares of these regressions were also appreciable; the lowest R square was for the monthly treasury yield regression (10%) while the highest R square, which was for the S&P index, attained 50%. The VEC predictive performance can be compared with the naive forecasting strategy that consists of using the last observed range to predict the next range. Table 9 clearly shows that the naive autoregressive approach based on past data provided less precise predictions. All the tests mentioned above supported this outcome: the Wald test always suggested a beta significantly different from one, while the R squares were much lower and the root-mean-square error (RMSE) was always higher. These results suggest that even a parsimonious specification of the vector autoregressive modelling with error correction is sufficient to capture the information content of high and low prices and has a significant predictive ability.

[23] We also used the regression approach to analyse high and low forecasts separately. In particular, we analysed the high-to-high and low-to-low price changes. Moreover, we conducted a regression-based test à la Fair-Shiller (1990), where the actual range (dependent variable) is regressed on diverse forecasted ranges. This permitted us to contrast the explanatory power of the different methods. These additional results (available upon request) largely confirmed the results presented in table 9.

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 timing of high and low prices is characterised by microstructure and behavioural aspects such as overnight non-trading time, trading intensity in the different world 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. We discuss some of the possible economic explanations and find that positive autocorrelation evokes information frictions (extended process of adjustment to new information, information cascades and leakages), herding behaviour and temporary trends. 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-variant market uncertainty and microstructure issues can cause high and low prices to deviate temporarily 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, daily extremes are clustered within the few minutes after news announcements. Unemployment Rate, Nonfarm Payrolls and Consumer Price Index bulletins are responsible for 26% to 58% of the daily extremes. On the other hand, an unexpected component in the news announcement will exert a significant impact on extreme price formation. "Good news" typically represents good news for the US dollar but bad news for equity and bond values. Thus, good news tends to move the high-low boundaries upward in foreign exchanges and downward in equity and bond futures. Furthermore, news impacts differ across markets. Unanticipated news components and simple news announcements impact more strongly on low (high) prices in equity and bond (foreign exchange) markets.

The third main contribution of this research is to provide evidence of the predictability of extreme prices. We propose a simple method of modelling high and low prices: 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 VEC is provided.

A better understanding of the information content of extreme prices is relevant for many different areas of finance and economics. It goes far beyond mere speculative use. The stylised facts documented in this research can be used in many areas and for many other purposes, in particular risk analysis and management (e.g. hedging, portfolio insurance and guaranteed products), derivatives (e.g. exotic options), and decision-making process (e.g. as a timing indicator and in scenario analysis). Future research could 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 of these questions go beyond the research objectives defined for this project. We therefore leave a systematic examination of these issues for upcoming research.

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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: Estimates from the VEC models

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

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

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

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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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	γ_1	γ_2	γ_3	γ_4	γ_5	λ_1	λ_2	λ_3	λ_4	λ_5	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 6: 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 mean 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[1]	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. [2]	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%**
ISM 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[3]	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[4]	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, the 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 7: News announcements effect estimated with the VEC model

This table shows the estimated coefficients for the following VEC regressions:

$$\mathbf{\Delta p}_t = \boldsymbol{\alpha}\left(\boldsymbol{\beta}'\mathbf{p}_t - \boldsymbol{\mu}\right) + \sum_{k=1}^{K-1} \mathbf{\Gamma}_k \mathbf{\Delta p}_{t-k} + \mathbf{\Psi d}_t + \mathbf{e}_t$$

where the vector of dependent variables is composed of $\mathbf{\Delta p}_t = \left(\Delta p_t^H, \Delta p_t^L\right)'$, i.e. the logarithmic high-to-high and low-to-low price change between t and $t-1$; $\mathbf{e}_t$ is the residual matrix; $\mathbf{\Psi}$ is a $2xk$ matrix of prameters and $\mathbf{d}_t$ is a $2xk$ matrix containing k dummy variables that individually equal one if the news item k is announced at time t, zero otherwise. k is equal to 25, 24 and 23 for the CHF/USD spot exchange rates (CHF/USD), treasury notes (TY) and S&P futures (SP), respectively. Only the coefficients of the exogenous variables are shown, i.e. the estimated coefficients related to announcement effects (Ψ). ** (*) indicates that the parameter is significant at least at 1% (5%) probability.

	CHF/USD		SP		TY	
Announcement	High	Low	High	Low	High	Low
Business Inv.	0.83	-0.15	0.36	-0.49	-0.16	-0.37
Capacity Util.	-5.15	-5.85			0.75	0.51
Construction.	-0.37	-1.46	1.84	1.91	0.65	0.91
Cons. Conf.	-0.18	-0.88	0.1	-0.73	0.75*	0.06
C.P.I.	0.03	-0.6	-0.12	-1.25	0.14	-1.18**
Credit	0.55	-0.16	-1.21	-0.55		
Durable Goods	0.4	-0.99	0.26	-1.09	0.69*	-0.22
Factory Orders	0.85	-0.99	0.25	0.43	-0.2	-0.35
FOMC target	1.05	0.19	3.05**	0.97	-0.15	0.2
GDP Adv.	2.54**	-0.08	2.87*	-1.15	2.24**	-0.98
GDP Prel.	1.99*	0.42	-0.74	-0.75	0.37	-0.24
GDP Final	-0.34	-1.09	1.65	1.01	0.32	-0.38
Trade Balance	1.18*	-1.16*	-0.75	-0.96	0.19	-0.09
Hausing Starts	0.77	-0.86	0.52	0.96	0.29	0.05
Industrial Prod.	5.94	5.1			-0.35	-0.51
ISM Index	1.18	0.15	-1.33	-2.49	0.42	-0.67
Leaders Indic.	0.92	-0.23	0.43	0.43	0.58	0.26
New Home S.	0.5	-0.1	0.3	0.29	0.02	-0.03
Nonfarm Payr.	-1.16	-4	3.2	-7.96	6.46**	3.76
P.C.E.	6.38	1.02	-0.6	0.22	0.43	0.36
Personal Inc.	-5.46	-1.7	1.28	1.73*	0.32	0.25
P.P.I.	0.08	-1.49**	0.63	-0.74	1.79**	-0.04
Retail Sales	1.41**	0.04	1.93*	1.7	-0.49	-1.64**
Unemployment	2.83	3.3	0.01	6.27	-3.89	-5.60**
Adj. R-sq.	0.23	0.17	0.12	0.13	0.16	0.08
Schwarz SC	6.26	6.4	7.17	7.52	5.64	5.71
Coeff. Mean	0.70	-0.48	0.63	-0.10	0.49	-0.26
Coeff. Stdev	2.56	2.05	1.32	2.48	1.70	1.53
Nbr Significant	4	2	3	1	5	3

Table 8: Surprise effect estimated with the VEC model

This table shows the estimated coefficients for the following VEC regressions:

$$\mathbf{\Delta p}_t = \boldsymbol{\alpha}\left(\boldsymbol{\beta}'\mathbf{p}_t - \boldsymbol{\mu}\right) + \sum_{k=1}^{K-1} \mathbf{\Gamma}_k \mathbf{\Delta p}_{t-k} + \mathbf{\Omega}\mathbf{S}_{t,i} + \mathbf{e}_t$$

where the vector of dependent variables is composed of $\mathbf{\Delta p}_t = \left(\Delta p_t^H, \Delta p_t^L\right)'$, i.e. the logarithmic high-to-high and low-to-low price change between t and $t-1$; $\mathbf{e}_t$ is the residuals matrix. $\mathbf{\Omega}$ is a $2xk$ matrix of prameters and $\mathbf{S}_{t,i}$ is a $2x1$ matrix of the standardised surprise componenent in the news bulletin i released in t. On non-announcement days, the surprise component is set to zero. Only the coefficients of the exogenous variables are shown, i.e. the estimated coefficients related to announcement effects (Ω). ** (*) indicates that the parameter is significant at least at 1% (5%) probability.

	CHF/USD		SP		TY	
Announcement	High	Low	High	Low	High	Low
Business Inv.	-0.34	-0.78	-0.42	-0.91	0.2	0.3
Capacity Util.	-0.06	-0.32			-0.41	-0.95*
Construction.	-0.75	-0.32	-0.57	-0.81	-0.2	-0.11
Cons. Conf.	1.10*	1.22*	1	1.62	-1.35**	-1.33**
C.P.I.	0.73	0.1	-1.70*	-2.70**	-0.03	-0.18
Credit	0.58	0.46	-0.19	-0.77		
Durable Goods	0.77	0.57	-0.93	-0.88	-0.79**	-1.06**
Factory Orders	-0.5	-0.81	-0.6	-0.86	-0.56	-0.70*
FOMC target	1.05	0.41	1.25	-2.65*	0.81	-0.38
GDP Adv.	-2.28*	-1.77	-2.01	0.39	-0.73	0.13
GDP Prel.	-2.6	-2.47	0.6	0.37	0.49	0.61
GDP Final	-0.09	1.06	-2.53	-1.12	0.08	0.45
Trade Balance	0.93*	1.00*	3.05**	2.21*	0.02	-0.21
Hausing Starts	0.31	-0.21	-0.11	-0.71	-0.05	0.01
Industrial Prod.	1.04	0.69			-0.07	0.3
ISM Index	1.01*	0.54	-0.33	0.63	-1.62**	-1.38**
Leaders Indic.	0.44	0.23	0.52	0.4	-0.42	-0.07
New Home S.	0.68	0.55	-1.02	-0.55	-0.47	-0.70*
Nonfarm Payr.	1.02*	1.52**	-0.93	-1.41	-2.40**	-2.01**
P.C.E.	0.34	0.84	-0.51	0.47	-0.15	-0.23
Personal Inc.	0.6	0.2	1.22	1.68*	-0.1	-0.21
P.P.I.	0.24	-0.34	0.54	-1.41	-0.69*	-0.55
Retail Sales	0.09	0.63	-0.68	0.11	-1.30**	-1.20**
Unemployment	0.95*	0.03	0.24	-0.68	-0.36	-1.14**
Adj. R-sq.	0.22	0.17	0.12	0.13	0.16	0.09
Schwarz SC	6.26	6.4	7.17	7.52	5.63	5.69
Coeff. Mean	0.22	0.13	-0.19	-0.35	-0.44	-0.46
Coeff. Stdev	0.97	0.92	1.22	1.26	0.71	0.67
Nbr Significant	6	3	2	4	6	9

Table 9: Out-of-the-sample forecasts

This table shows the out-of-sample forecasts based on the VEC model. These VEC predictions (VEC) are compared with a naive forecasting strategy (Naive) and a VEC implementation with exogenous variables that are variable indicators for news announcements (VEC-news). The daily and monthly timeframe is considered ("day" or "month" in the model column). 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). The second column shows the out-sample-of-sample periods ("O-o-S period"). On the left-hand side, this table shows the hit ratio in order to assess how many times forecasts correctly predict the direction of high-to-high (HH) and low-to-low (LL) price changes. The "close-within-range" and "mid-price-within-range" hit ratios 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 naive and VEC 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 naive 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.

Model	O-o-S period	HH	LL	Close within Range	Mid-Price within Range	Alpha	Beta	R2	Wald test β=1	RMSE (%)
CHF/USD										
VEC day	12/93-12/03	0.62**	0.62**	0.59*	0.77**	0.00	0.96	0.12	0.56	0.22
VEC day	9/00-5/03	0.67**	0.65**	0.58*	0.74**	0.00	0.93	0.22	0.45	0.23
VEC-news day	9/00-5/03	0.66**	0.64**	0.59*	0.76**	0.00	0.92	0.06	16**	0.28
Naïve day	12/93-12/03	0.50	0.48	0.54	0.7	0.00	0.25	0.06	541**	0.30
Naïve day	9/00-5/03	0.47	0.48	0.53	0.69	0.00	0.03	0.01	695**	0.38
VEC month	1/99-12/03	0.71**	0.60**	0.54*	0.79**	0.00	1.09	0.24	0.25	1.34
Naïve month	1/99-12/03	0.56	0.59	0.48	0.63	0.06	-0.19	0.04	104**	2.12
SP										
VEC day	11/89.5/03	0.61**	0.59*	0.70*	0.73**	0.00	0.99	0.5	0.10	0.26
VEC day	9/00-5/03	0.61**	0.61**	0.59*	0.64	0.00	0.99	0.37	0.87	0.28
VEC-news day	9/00-5/03	0.60**	0.60*	0.53	0.63	0.00	1.15	0.39	3.42*	0.27
Naïve day	11/89.5/03	0.52	0.53	0.68*	0.59	0.00	0.50	0.16	178**	0.35
Naïve day	9/00-5/03	0.52	0.52	0.48	0.59	0.01	0.40	0.25	112**	0.34
VEC month	1/95-5/03	0.74**	0.68**	0.53**	0.81**	0.00	0.98	0.5	0.05	2.98
Naïve month	1/95-5/04	0.68	0.6	0.44	0.64	0.06	0.34	0.11	29**	4.26
TY										
VEC day	11/89.5/03	0.60**	0.58**	0.49	0.63**	0.00	0.91	0.13	3.26	0.11
VEC day	9/00-5/03	0.60**	0.57**	0.49	0.59*	0.00	0.85	0.16	3.96	0.12
VEC-news day	9/00-5/03	0.60**	0.57**	0.42	0.53	0.01	0.77	0.15	10**	0.13
Naïve day	11/89.5/03	0.49	0.5	0.47	0.55	0.00	0.19	0.04	1075**	0.15
Naïve day	9/00-5/03	0.48	0.5	0.44	0.53	0.00	0.19	0.04	331**	0.14
VEC month	1/95-5/03	0.70**	0.61*	0.58	0.74**	0.00	0.98	0.10	0.06	1.41
Naïve month	1/95-5/04	0.53	0.57	0.47	0.62	0.03	0.08	0.01	95**	1.98

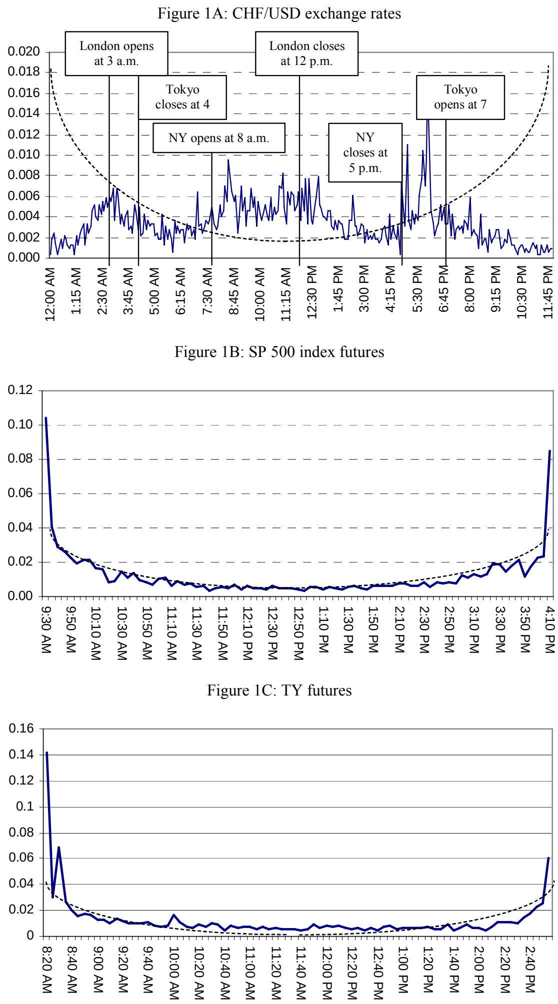


Figure 1: These three figures show the relative frequency of intraday occurrence of the highest traded price for the CHF/USD spot exchange rate (Figure 1A), S&P 500 index futures during open-outcry trading hours (Figure 1B) and treasury yields futures (Figure 1C). The dotted grey lines plot the intraday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

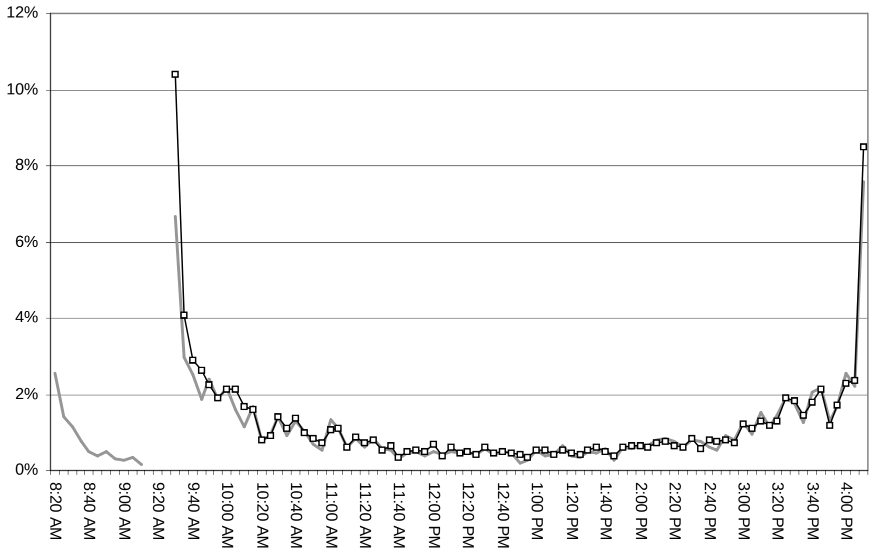


Figure 2: This figure shows the relative frequency of intraday occurrence of the highest traded price for the S&P 500 Index futures. Two trading periods are considered: first, open-outcry trading hours (black line marked by white squares); second, open-outcry trading hours extended by the last hour of 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). Trading times are indicated in terms of Eastern Time (ET).

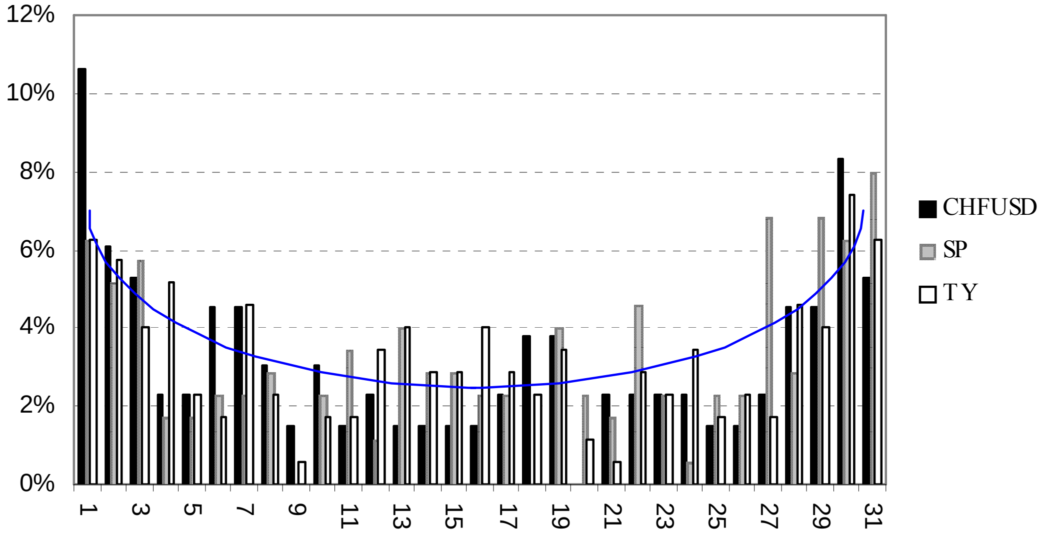


Figure 3: This figure shows the relative frequency of intra-month occurrence of the highest prices for the CHF/USD spot exchange rate (black bars), S&P 500 index futures (grey bars) and treasury yields futures (white bars). The black line plots the intra-month timing of extreme prices implied by the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

Figure 4.1.: Response to a Shock of Daily High Price

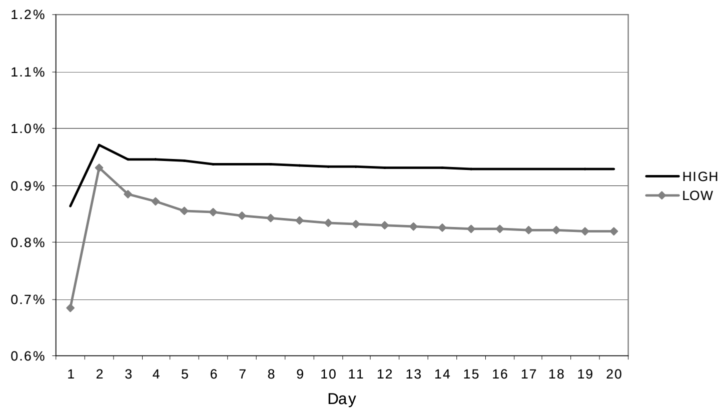


Figure 4.2.: Response to a Shock of Daily Low Price

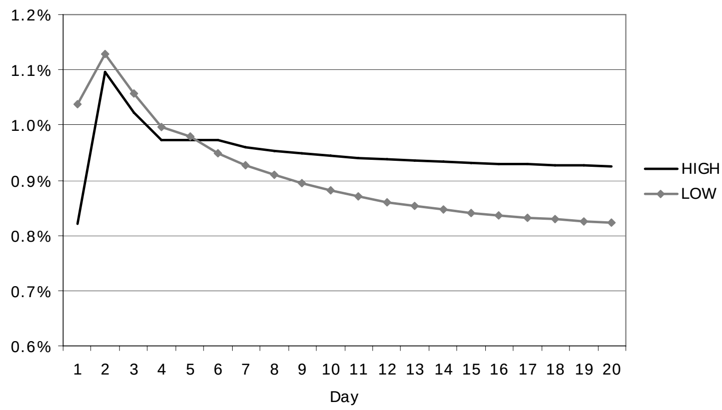
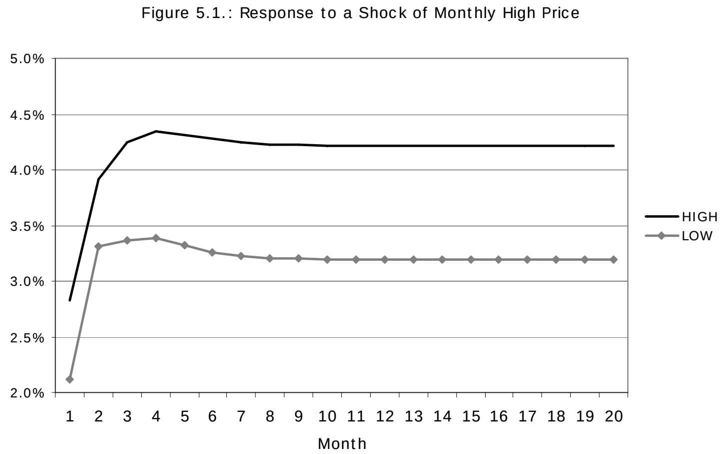


Figure 4: Generalized Impulse-Response Analysis for Daily Shocks in the S&P 500 Index Futures Market



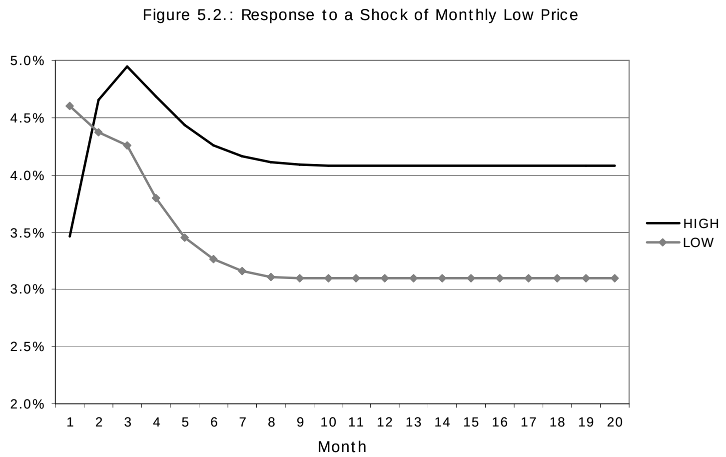


Figure 5: Generalized Impulse-Response Analysis for Monthly Shocks in the S&P 500 Index Futures