Disposition Effect and Asymmetric Volatility of Individual Stocks

Claudio M. P. Cunha – PUC-Rio

Abstract – We investigate asymmetric volatility effect (the negative partial correlation between volatility and lagged return), conditioning volatility changes to the sign of cumulative return over the past ten days. We find that negative cumulative past returns are fundamental to understand asymmetric volatility. However we also find that asymmetric volatility can not be interpreted as simply a response to cumulative returns instead of last return. We explain the role of past cumulative return based on the behavioral bias labeled "disposition effect" by Shefrin and Statman (1985). Using a measure of average capital gain instead of cumulative return, to proxy for intensity of disposition effect, as proposed by Grinblatt and Han (2005), we confirm our conjecture that for negative capital gain volatility is more sensitive to return shocks. But we also find, consistently with our argument, that for positive capital gain volatility is less sensitive to return shocks.

JEL classification: G11, G12

Key words: asymmetric volatility, behavioral finance, disposition effect

Resumo – Nós investigamos a o efeito de volatilidade assimétrica (a correlação parcial negativa entre volatilidade e retorno no período anterior), condicionando variações da volatilidade ao sinal do retorno acumulado nos últimos dez dias. Encontramos que retornos acumulados negativos são fundamentais para compreender a volatilidade assimétrica. Entretanto, também verificamos que a volatilidade assimétrica não pode ser interpretada como simplesmente uma resposta a retornos acumulados ao invés do último retorno. Explicamos o papel do retorno acumulado nos baseando no viés comportamental denominado "efeito disposição" por Shefrin e Statman (1985). Usando uma medida ponderada de ganho de capital no lugar de retorno acumulado, como aproximação da intensidade do efeito disposição, conforme proposto por Grinblatt e Han (2005), confirmamos nossa conjectura de que para ganho de capital negativo a volatilidade é mais sensível a choques de retorno. Adicionalmente encontramos, consistentemente com nossa argumentação, que para ganho de capital positivo a volatilidade é menos sensível a choques de retorno.

Classificação JEL: G11, G12

Palavras-chave: volatilidade assimétrica, finanças comportamentais, efeito disposição

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1. Introduction

It is well documented in finance literature that the standard deviation of returns for a stock (from now on, volatility of the stock) changes over time and presents clustering (that is, after abnormally high absolute returns, other abnormally high absolute returns are more probable). Another stylized fact is the asymmetric volatility, which is a negative partial correlation between volatility and lagged returns. Nevertheless, the subjacent economic factors that determine these stylized facts are not well known yet. The focus of the present study is on these subjacent economic factors.

The clustering behavior of volatility has been successfully reflected within the Auto-regressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982). This model was generalized by Bollerslev (1986), allowing volatility to respond not only to abnormal past absolute returns, but also to past volatility, in the General Autoregressive Conditional Heteroskedasticity (GARCH).[1] Modifications of the GARCH model also capture asymmetric volatility effect. But these models assume changing, clustering and asymmetric volatility, shedding no light on the subjacent processes.

Avramov, Chordia and Goyal (2006a) (henceforth ACG) provided empirical evidence that the combination of signs of current return and cumulative past returns over a few days plays a role in conditional volatility. They explained their result based on behavioral biases. However their study was focused on the contribution to asymmetric volatility of sell trades, that is, trades initiated by a sell offer. So, all their results are conditioned on the fraction of sell trades over total trades. This motivated us to study the effect of these combinations of signs on asymmetric volatility independently of volume data. Our results diverge from ACG. While for ACG volatility increases more when cumulative past return is positive and current return is negative, for us volatility increases more when cumulative negative return and current return are negative. Our results also reject that asymmetric volatility is associated only with cumulative past returns.

As ACG we rely on "disposition effect" to explain the results. The disposition effect, labeled by Shefrin and Statman (1985), is the tendency of investors to hold stocks with negative cumulative returns ("losers") for too long and sell stocks with positive cumulative returns ("winners") too early. Taking past cumulative returns is a way to classify winners and losers. For losers, investors subject to disposition effect (henceforth DE investors) hold their stocks, resulting in illiquidity for the stock, mainly for negative current returns. If demand shocks cause price changes as in Campbell, Grossman and Wang (1993), then these price changes will be more intense due to illiquidity.

We may analogously reason that for winner stocks, DE investors are willing to sell their shares, making the market more liquid for the stock. Then volatility should

[1] As emphasized by Enders (2004): "The benefits of the GARCH model should be clear; a high-order ARCH model may have a more parsimonious GARCH representation that is much easier to identify and estimate."

increase less in the presence of demand shocks. Our results, however, do not support this part of the reasoning. We attribute this to the limited ability of returns over 10 days to classify winners and losers from the perspective of DE investors. We then propose the use of a measure of capital gain based on a longer sequence of past data, similar to the one proposed by Grinblatt and Han (2005) on a study about the relation between disposition effect and momentum.[2] When we combine the signs of current return and capital gain, we indeed show that volatility responds more intensively to shocks when capital gain and current return are both negative, and responds less intensively when both are positive.

The rest of the article proceeds as follows. In the next section data used in the analyses is described. In section 3 we present the results on how the combination of signs of current returns and cumulative returns over past ten days affects asymmetric volatility. In section 4 we develop our explanation based on disposition effect and show that using capital gain instead of cumulative returns over ten days, our explanation is valid for negative and positive capital gains. Section 5 concludes.

2. Data

We use the daily returns, shares outstanding and trading volumes from CRSP database covering NYSE stocks over the sample period from January of 1987 through December of 1998. Data from 1987 is only used to estimate reference prices in a way similar to Grinblatt and Han (2005)[3]. Our sample comprises only common stocks listed at NYSE with data available for every trading day in the selected period. Thus, all stocks in the sample are listed at NYSE for at least one year, and have survived for a period of 11 years. This sample is convenient because it excludes the crash of October of 1987, [4] and the core of the burst and blow of the NASDAQ bubble. It also removes firms that have gone through recent IPO, that have been delisted in the period, and that are very illiquid. This enhances the focus on idiosyncratic volatility driven by exogenous demand shocks. The final sample comprehends 844 stocks.

We classified each observation (that is, each stock – date), by size, within the cross-section of each date. Stocks were classified into five equal sized groups[5]. The proxy for size was market capitalization computed as the product of share price by the

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[2] Momentum is the positive correlation of cumulative returns measured over periods of three to twelve months. It was first reported by Jegadeesh and Titman (1993).

[3] The sample period, then, goes from January of 1988 through December of 1998. This is the same period used by Avramov, Chordia and Goyal (2006a).

[4] Campbell, Grossman and Wang (1993), analyzing the reversal of returns due to liquidity trading, which is the source of volatility we are interested in, noticed that their analysis, with a sample period from 1962 through 1988, was "dominated by a few observations around the stock market crash of October 19, 1987". For this reason they removed from their sample all the data starting from October 1st, 1987. Since they mention "a few observations around" the crash, we think it is satisfactory to start our sample in the beginning of 1988.

[5] The group with smaller firms had fewer observations, since 844 is not a multiple of 5.

number of shares outstanding on that date.[6] Summary statistics for each size group are presented in Table I. Except for the number of stocks (which is fixed, despite the stocks in each group may change), values presented in Table I are mean values for respective variable, with standard deviation in parenthesis, calculated with all observations (stock – dates).[7] The values of turnover are daily turnover multiplied by 255, to get an approximate value of the corresponding yearly turnover. Market Capitalization is in billions of dollars. Realized volatility is calculated for each observation (stock – date) using the 255 past returns. Because realized volatility and market capitalization are very persistent at daily frequency, we omit standard deviations.

Table I – Summary statistics by size group

	1 (small)	2	3	4	5 (big)
no. stocks	**168**	**169**	**169**	**169**	**169**
return	**0.050%** **(3.221%)**	**0.063%** **(2.124%)**	**0.065%** **(1.919%)**	**0.073%** **(1.767%)**	**0.088%** **(1.651%)**
|return|	**1.787%** **(2.681%)**	**1.343%** **(1.647%)**	**1.273%** **(1.438%)**	**1.212%** **(1.288%)**	**1.182%** **(1.157%)**
realized volatility	**2.693%**	**1.945%**	**1.808%**	**1.710%**	**1.618%**
turnover	**50.8%** **(223.7%)**	**64.1%** **(134.7%)**	**75.4%** **(130.3%)**	**76.6%** **(109.2%)**	**66.8%** **(91.4%)**
market capitalization	**0.082**	**0.351**	**0.994**	**2.73**	**15.4**

3. Results

Avramov, Chordia and Goyal (2006a), henceforth ACG, find evidence that dummies defined by combining the signs of current daily return and cumulative returns over the past ten days are relevant for conditional volatility. Since there are four combinations of the signs of these two variables (we will refer to each combination as a regime), they defined four dummies. They argue that due to behavioral biases, market dynamics is different for each regime. For instance, ACG argued that the regime characterized by positive unexpected current daily return and negative cumulative return over the past ten days is dominated by contrarian trading of informed investors. As their study was about "the impact of trades on daily volatility", they evaluated how these dummies affected the relation between conditional volatility and measures of daily trading. (They focused on the ratio of sell trades over total trades.)

This raises the question whether the same dummies (or the same definition of regimes) affect conditional volatility independently of trading volume measures. We are

[6] This is not the best alternative from the econometric point of view, because size classification will be correlated with past cumulative return. We should use, for instance, the market capitalization at the end of previous year. We chose this way because it was easier and faster to compute. We don not believe that any significant bias was introduced, also because results were similar for the five groups.

[7] Because stocks are classified by group every day, it does not make sense to calculate de mean for each variable and then the mean of the variables in the size group.

especially interested on how asymmetric volatility (the negative auto-correlation between volatility and lagged returns)[8] is affected by cumulative past returns. One approach to evaluate asymmetric volatility is estimating the parameters of the following regression:

$$\sigma^{p}_{j,t+1} = \alpha + \left(\theta_0 + \theta_1 I^{*}_{j,t}\right)\cdot\left|\varepsilon_{j,t}\right| + \sum_{i}\phi_i \sigma^{p}_{j,t-i} + v_{j,t} \tag{1}$$

where j indexes stocks, t indexes trading days, r_t is the unexpected return, $\sigma^{p}_{j,t}$ is the conditional volatility, $v_{j,t}$ is an error term, $I^{*}_{j,t}$ is a dummy, that equals 1 if r_t is negative, and equals zero otherwise, and α, θ_0, θ_1, and ϕ_i are parameters to be estimated. This specification is similar to the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model developed by Bollerslev (1986). The main difference is the inclusion of a dummy to account for asymmetry in the partial correlation between past returns and volatility.[9] The existence of asymmetric volatility effect is characterized by a statistically significant negative parameter θ_1.

We expand equation (1) to include the different dummies defined similarly to ACG. Also, to avoid the use of a large set of lags of our proxy for volatility, we follow Corsi (2009) and use a cascade model. We build the cascade model with two past realized volatilities computed at periods of 22 trading days (approximately 1 month), and 128 trading days (approximately 1 semester). Thus, we will estimate volatility as:

$$\sigma^{p}_{j,t+1} = \alpha + \left(\theta_0 + \theta_1 I^{nn}_{j,t} + \theta_2 I^{pn}_{j,t} + \theta_3 I^{pp}_{j,t}\right)\cdot\left|\varepsilon_{j,t}\right| + \phi_1 RV^{22}_{j,t} + \phi_2 RV^{128}_{j,t} + v_{j,t} \tag{2}$$

where θ_1, θ_2 and θ_3 are additional parameters to be estimated, and $RV^{D}_{j,t}$ is the realized volatility of the D days starting at $t - D + 1$. The variables $I^{ss}_{j,t}$ are dummies defined as follows: $I^{nn}_{j,t} = 1$ if past cumulative return and current return are negative; $I^{pn}_{j,t} = 1$ if past cumulative return is positive and current return is negative, and $I^{pp}_{j,t} = 1$ if past cumulative return and current return are positive. As ACG past cumulative returns are calculated for the ten previous days.[10]

In essence, our null hypothesis is that the series of daily returns is a martingale, and volatility is an auto-regressive moving average (ARMA) process. This means that we may use simple returns directly as unexpected returns. There is a whole literature on the predictability of stock-returns, the so called "anomalies" to the Efficient Markets Hypothesis. Schwert (2003) presents a review of this literature. This challenges our choice of using returns directly as unexpected returns. Additionally, mean returns should pay a premium for risk that should be greater than the risk free rate. Then, unexpected returns should at least discount this premium. However there is no

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[8] See, for instance, Nelson (1991) for empirical evidence of asymmetric volatility in daily returns of the value weighed CRSP index. Avramov, Chordia and Goyal (2006a) provide empirical evidence of asymmetric volatility in daily returns for individual stocks.

[9] This specification is also referred to as threshold-GARCH, or TARCH.

[10] Instead of four dummies, we use only three in equation (3), to avoid linear dependence. ACG used the four regime dummies because the dummies multiplied their sells trade measure, avoiding linear dependence.

agreement in finance literature about the best procedure to estimate the risk premium, at least because it is not clear whether there is risk associated to the excess returns of anomalies.[11] On the other hand, supporting our approach, there is empirical evidence that the unconditional auto-correlation of individual stock returns is "both statistically and economically insignificant" (Lo and MacKinlay, 1988), and if they are statistically significant as for French and Roll (1986), then, "since the average autocorrelations are small in magnitude, it is hard to gauge their economic significance".[12] Indeed, mean expected return is much lower than the standard deviation of daily returns, as we see in Table I. We are actually interested in changes of the standard deviation of stock returns, or the volatility. For this reason, trying to adjust returns for possible violations of the martingale hypothesis may add noise that will distort the measure we are interested in.

The absolute value of unexpected return has been used as a proxy for daily volatility at least since Schwert (1990), and has also been used by ACG. The use of a direct measure of volatility allows pooling data in our analyses. Because we are interested in performing analyses in the cross-section of stocks, pooled data analyses are preferable. The alternative would be individual time-series analysis of each stock, using a modified GARCH model. But this way we would obtain individual parameters for each stock and would not be able to make inference about the mean parameter, because the time-series are not independent.[13] To keep consistency, we calculate realized volatility as the mean of absolute returns, instead of the mean of the squares of demeaned returns.

With the considerations above, we arrive at the following equation, for which we will estimate the parameters:

$$\left|r_{j,t+1}\right| = \alpha + \left(\theta_0 + \theta_1 I_{j,t}^{nn} + \theta_2 I_{j,t}^{pn} + \theta_3 I_{j,t}^{pp}\right)\cdot\left|r_{j,t}\right| + \phi_1 \sum_{i=0}^{21}\left|r_{j,t-i}\right| + \phi_2 \sum_{i=0}^{127}\left|r_{j,t-i}\right| + v_{j,t} \quad (3)$$

Table II presents the estimated parameters in equation (3). In parenthesis are t statistics using standard errors robust to heteorskedasticity. The coefficient θ_1 is highly statistically significant for all size groups. The coefficient θ_2, when statistically significant, is negative. This means that cumulative past returns plays a major role in asymmetric volatility. One might argue that asymmetric volatility is actually related to past returns. However, if this was the case, coefficient θ_3 should be unambiguously

[11] In the words of Schwert (2003) "They [the anomalies] indicate either market inefficiency (profit opportunities) or inadequacy in the underlying asset-pricing model."

[12] This explains why we do not estimate unexpected returns as the residuals of an auto-correlation process with many lags of returns, as Avramov, Chordia and Goyal (2006a). Indeed they allege to be following Schwert (1990), but this author was working with an aggregate market index (the CRSP value weighed index), for which auto-correlations are statistically and economically significant.

[13] A better direct measure of daily volatility is the realized daily volatility calculated from intra-day returns series, as proposed by Andersen and Bollerslev (1998). But working with a large set of stocks and a time span of many years makes this sort of analysis virtually unviable, mainly if we want to expand the analysis backward in time.

negative. The question raised is: why negative cumulative past returns increases the impact of negative current returns?[14]

Table II – Estimated parameters of equation (3).					
Size Group	5 (big)	4	3	2	1 (small)
θ_1	0,079 (16,81)	0,086 (17,06)	0,072 (13,09)	0,074 (10,71)	0,082 (6,98)
θ_2	0,004 (1,10)	-0,003 (-0,76)	-0,017 (-3,46)	-0,021 (-4,28)	-0,041 (-5,17)
θ_3	-0,017 (-4,96)	-0,009 (-2,35)	-0,003 (-0,58)	0,006 (1,19)	0,029 (3,77)
θ_0	0,080 (26,39)	0,092 (27,52)	0,097 (25,31)	0,104 (26,08)	0,124 (22,45)
ϕ_1	0,408 (55,81)	0,386 (51,11)	0,370 (43,15)	0,352 (40,86)	0,299 (27,45)
ϕ_2	0,336 (44,02)	0,370 (47,31)	0,411 (46,80)	0,425 (44,34)	0,512 (45,29)
α	0,002 (31,07)	0,002 (26,35)	0,001 (21,38)	0,001 (20,10)	0,001 (9,30)
R^2	9,48%	11,59%	13,41%	14,4%	19,6%

4. **An Explanation**

Under no-arbitrage hypothesis, the variance of returns is directly related to information flow (Ross, 1989). However, empirical evidence points in the opposite direction, that is, most of volatility is not related to information flow. French and Roll (1986) and Roll (1988) present some evidence that public news plays a minor role in price changes. Shiller (1981) and West (1988) show that prices volatility in the stock market are much greater than the ex-post volatility of fundamental value calculated with the discount value of dividends. Prices changes not based on public information arise to accommodate trading initiated by private motivation, which we will call demand shocks. [15] Although it seems that other investors could arbitrage on these prices deviations, market frictions constrain arbitrage strategies. For instance, if there are investors with private information, there is a problem of adverse selection that limits

[14] The explanation by Avramov, Chordia and Goyal (2006a) for the differences in volatility behavior for different regimes does not apply. First because it is conditioned on the fraction of sell trades. Second because they find higher response to current negative returns when past returns are positive.

[15] Grossman and Stiglitz (1980) simply assume the supply of the stock is random. This is compatible with a fixed supply of the stock and some investors with a random demand. Kyle (1985) labels these investors with random demand as “noise traders”. Glosten and Milgrom (1985) assume that some investors may be subject to stochastic shocks in their preferences. Wang (1994) works with incomplete markets and asymmetric information. In his framework demand shocks may arise either based on private information or for hedge motives after idiosyncratic shocks in private investment opportunities.

arbitrage strategies against demand shocks.[16] Another approach is that there are investors who are misinformed about fundamental value of the stock. Arbitrage may be limited due to limited funding or short horizon of arbitrageurs, since they do not know for how long they must bear their bet against these misinformed noise traders, who may even increase their bets.[17]

If price changes are not related to news, but to demand shocks, then they tend to be reversed, as shown by Campbell, Grossman and Wang (1993).[18] One may expect that if the market for a stock is very liquid, demand shocks are easily accommodated, and associated contemporaneous price changes will be small as well as subsequent reversals. Conversely, when market is illiquid, the magnitude of contemporaneous price changes and related reversals should be greater. This relation between demand shocks, illiquidity and reversals has been shown by Avramov, Chordia and Goyal (2006b). So, conditional volatility (the standard deviation of relative price changes, i.e. returns), is expected to be positively correlated with illiquidity. Additionally, the response of conditional volatility to lagged returns tends to be higher. So, returning to the question raised in the end of Section 3, if past returns affect illiquidity, they do affect the intensity of volatility's response to lagged returns. Specifically, we are able to answer why negative cumulative past returns increases the impact of negative current returns if we identify the reason why illiquidity should be higher after negative cumulative returns. [19]

Since the Prospect Theory by Kahneman and Tversky (1979), there has been a growing literature on how agents may be influenced in their decisions by behavioral biases. The "disposition effect", labeled by Shefrin and Statman (1985), is a behavioral bias characterized by the tendency of investors to hold stocks with negative cumulative returns ("losers") for too long and sell stocks with positive cumulative returns ("winners") too early.[20] Odean (1988) provides empirical evidence that many individual

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[16] This is the approach used by the authors mentioned in the previous foot note.

[17] This approach is represented by DeLong, Shleifer, Summers and Wadmann (1990), and Shleifer and Vishny (1997).

[18] Here we mention "news", generically, instead of "public news", because a private motivation to trend may be private information. In this case price changes are not expected to reverse, as shown by Llorente, Michaely, Saar and Wang (2002).

[19] We will again justify our preference for returns in equation (3), instead of unexpected returns taken as the residuals of an auto-correlation process. Volatility is generally defined as the standard deviation of returns, as pointed by Poon and Granger (2003), in a review of volatility forecasting in financial markets. We are arguing that time changes in this variable are due to changes in expected return associated with liquidity trading. If we remove the auto-correlated component of returns, the signal we want to capture is attenuated. The use of unexpected returns computed as the residuals of an auto-regressive process is best fitted to test the intertemporal relation between expected return and risk (standard deviation from expected returns).

[20] It combines two behavioral biases: loss aversion, proposed by Kahneman and Tversky (1979), and "mental accounting", proposed by Thaler (1980). Loss aversion is the reluctance to take decisions that represent sure losses, from the perspective agents frame the problem. Mental accounting is the tendency to evaluate risky decisions independently, i.e., creating a mental account for each decision. In the stock market context, investors subject to loss aversion would be reluctant, for example, to sell a stock with current price lower than the price they paid for that stock (which would be, in this case, the reference around which they frame their decisions). They would also feel riskier to continue holding a winning stock. Mental accounting prevents them from evaluating the best decision for their whole portfolio, leading them to evaluate stocks individually. Thus, DE investors sell winners and hold losers. Due to tax

investors are subject to this behavioral bias. Frazzini (2006) studies investment funds and also finds evidence of disposition effect on the decisions of professional asset managers. These evidences support the idea that disposition effect may be involved in a large proportion of trades, being capable of limiting arbitrage as proposed by Shleifer and Vishny (1997), and thus playing a role in asset pricing.[21]

In the presence of investors subject to disposition effect (henceforth DE investors.), market is very liquid for winner stocks, because DE investors are inclined to sell their shares. Positive demand shocks (that is demand shocks that cause price increase) are easily absorbed at small price changes. The trust of our argument is that DE behavior is not symmetric for winner stocks and loser stocks. If DE investors are losing on a stock, they do not want to either sell or buy shares of that stock; they just want to hold their current position. The market is then more illiquid for a past loser, and we find the link between past returns and illiquidity, and thus conditional volatility, that we were looking for.

The problem with the argument above is that for winner stocks we should expect DE investors to be more prone to sell their shares. The market for the stock would be then less illiquid, and conditional volatility should react less to demand shocks. This means that the sign of coefficient θ_3 in equation (3) should be negative, but in Table II this sign is ambiguous.

Core to the direction of the disposition effect (i.e. to the choice of selling quickly or holding the stock) is the reference from which DE investors frame the problem. Because DE investors are averse to losses, they want to sell a share if its current price is above the price they paid for it, and hold it if the current price is below. The difference between current and paid prices is the capital gain. The cumulative past return is a proxy for the capital gain.[22] The cumulative return over the 10 preceding days used in Section 3, to follow Avramov, Chordia and Goyal (2006a), is a rough proxy of capital gain. Griblatt and Han (2005), studying the relation between disposition effect and momentum, propose taking a weighed average of a long sequence of past prices. We take 250 days (approximately 1 year) backwards.[23] The weights are proxies for the quantity of shares that DE investors bought on date $t–k$, and still hold on date t, normalized so that the sum of weights equals one. Following this procedure, capital gain, labeled g_t, is computed as:

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benefits (the possibility of deducing realized losses from earnings), fully rational investors should at least combine the selling of winners and losers to minimize taxes, after adjusting for transaction costs. (See Shefrin and Statman, 1985).

[21] Indeed, Grinblatt and Han (2005) develop an equilibrium model considering disposition effect that explains "momentum" (the tendency of past winners to continue presenting higher returns, and past losers to continue presenting lower returns, first reported by Jegadeesh and Titman, 1993). They also provide empirical evidence supporting their proposition.

[22] Note that because dividends are not considered, capital gain over a period is usually not the same as the return. Additionally, the capital gain depends on the price paid, and not only on the recent returns. If the shares were bought too long ago, even after positive cumulative returns in the recent past, capital gain may be negative, depending on the whole history of returns since the purchasing day.

[23] Grinblatt and Han (2005) used 250 weeks (approximately 5 years). Using stocks with 5 years of data before 1988 would reduce too much our sample. Using 250 days makes the difference to taking the ten 10 past days, without reducing the sample.

$$g_{j,t} = \sum_{k=1}^{250} w_{j,t-k} \left[\prod_{n=0}^{k-1} \left(1 + r^*_{j,t-k}\right) - 1 \right] \tag{4a}$$

$$w_{j,t} = \frac{V_{j,t-k} \prod_{i=0}^{k-1} \left(1 - V_{j,t-i}\right)}{\sum_{k=1}^{250} \left[V_{j,t-k} \prod_{i=0}^{k-1} \left(1 - V_{j,t-i}\right) \right]} \tag{4b}$$

where $V_{j,t}$ is the turnover of stock j on date t, computed as the ratio of total shares traded on that day, by outstanding shares on that day, and $r^*_{j,t-k}$ is the ex-dividend return of stock j on date t.[24]

Table III presents the estimated parameters in equation (3), when dummies $I^{ss}_{j,t}$ are determined based on the signs of the capital gain $g_{j,t}$ instead of the cumulative return over the past ten days. The main difference between Table II and Table III is that in the later the sign of θ_3 is not ambiguous anymore. Indeed, as expected from our argument, it is negative, and statistically significant at 10% level for all size groups, and at 5% level for four of the five size groups.

Table III – Estimated parameters of equation (3), using Grinblatt and Han's (1985) capital gain g_t to determine the dummies $I^{ss}_{j,t}$

Size Group	5 (big)	4	3	2	1 (small)
θ_1	0,050 (8,44)	0,054 (9,33)	0,042 (6,63)	0,055 (7,30)	0,037 (3,49)
θ_2	0,021 (4,87)	0,009 (2,02)	0,003 (0,51)	-0,011 (-2,03)	-0,059 (-7,57)
θ_3	-0,026 (-6,68)	-0,033 (-8,11)	-0,020 (-4,35)	-0,009 (-1,71)	-0,026 (-3,43)
θ_0	0,090 (23,58)	0,108 (28,82)	0,108 (25,21)	0,112 (24,52)	0,145 (25,64)
ϕ_1	0,406 (55,74)	0,377 (50,10)	0,363 (42,78)	0,336 (38,91)	0,282 (25,65)
ϕ_2	0,332 (43,32)	0,371 (47,44)	0,412 (47,01)	0,428 (44,83)	0,521 (46,20)
α	0,002 (32,21)	0,002 (27,62)	0,001 (22,51)	0,002 (21,27)	0,001 (11,00)
R^2	9,38%	11,49%	13,29%	14,4%	19,5%

[24] Grinblatt and Han (2005) take the nominal prices at which stocks were actually traded. We believe this is not the best approach because there may be splits and grouping of shares that affect prices, but probably are adjusted in the reference price. It is important to remember that as in Griblatt and Han (2005), and consistent with empirical evidence from Odean (1998), investors subject to disposition effect are informed, and their demand function partly incorporates the demand function of arbitrageurs. Instead of using nominal trading prices, we use returns corrected for splits and groupings, but not adjusted for dividends. This way we capture the actual capital gain per share.

5. Conclusion

We presented empirical evidence that the intensity of asymmetric volatility effect depends on the sign of past cumulative returns. The greater partial correlation between volatility and return, in absolute value, occurs when the cumulative return in the past ten days and current return are both negative.

We explained this result as a consequence of the behavioral bias labeled disposition effect by Shefrin and Statman (1985). We argue that investors subject to disposition effect are more willing to sell winner stocks (those that provide capital gain), and more prone to hold their loser stocks (those that provide capital loss). The market is then illiquid for losers (stocks with negative cumulative returns), increasing the magnitude of price changes in the presence of demand shocks.

Grinblatt and Han (2005) proposes a procedure to estimate capital gain, and thus to evaluate whether investors subject to disposition effect are more willing to sell or to hold their shares. Using this procedure, we show that not only volatility increases more in the presence of capital loss and negative current return, but also, as expected from our explanation, that volatility increases less in the presence of positive capital gain and positive current return.

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