3
Cumulative returns and asymmetric volatility of stocks daily returns

3.1.
Introduction

The standard deviation of asset returns (from now on, volatility of the asset) is widely used as a prevailing variable to explain differences in mean returns. Thus, understanding and forecasting volatility changes becomes fundamental to finance, both in theory and in practice. It is well documented in finance literature that stocks volatility changes over time and presents clustering (that is, after abnormally high absolute returns, other abnormally high absolute returns are more probable). The clustering behavior of volatility has been successfully reflected within the Auto-regressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982).[1]

The objective of this study is to better understand under what conditions volatility clustering is more or less intense. Particularly, we will study the "asymmetric volatility effect", first reported by Black (1976). It is a well known stylized fact about volatility characterized by a negative partial correlation between volatility and lagged returns. That is, volatility increases more conditioned on negative shocks to prices. Modifications of the GARCH model, as the Exponential GARCH (EGARCH) model, developed by Nelson (1991), and the Threshold GARCH (TARCH) model, developed by Zakoïan (1994), capture this effect. Schwert (1990) use the absolute value of unexpected returns as a proxy of volatility, an empirical approach similar to the one used in this article, and also find a negative partial correlation between volatility and lagged returns.

[1] 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). 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."

The main result reported in this article is the amplification of asymmetric volatility effect conditioned on negative past returns. Our results also reject that asymmetric volatility is associated only with cumulative past returns. To obtain these results we use pooled OLS regressions applied to daily data. To work with pooled regressions, we avoid using volatility as latent variable. Instead, we define a proxy for volatility, which may be obtained directly from returns data. As Schwert (1990), we chose absolute returns.[2]

Avramov, Chordia and Goyal (2006), 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. ACG also followed Schwert (1990) by estimating variations in absolute returns as a proxy for volatility. However their study was focused on the contribution of sell trades (trades initiated by a sell offer) to asymmetric volatility. So, instead of using daily returns as explanatory variables, they used the daily product of returns by the ratio of sell trades over total trades. (Naturally interactions with dummies were also included.) This motivated us to study the effect of the combinations of signs of current and cumulative past returns on asymmetric volatility, without the sell trades ratio. (That is, using daily returns and its interactions with dummies as explanatory variables.) We find that volatility increases more responding to shocks in returns when current return and the cumulative return are both negative. (We take cumulative returns ranging from 1 to 255 days – approximately one year.)

Another important result concerns the combination of positive current return and positive cumulative return. Conditioned on this combination, the response of volatility to new shocks in returns is attenuated. However this result is not present when we take only few days of cumulative return. Additionally, this results shows up earlier (i.e., when cumulative periods are shorter) for large firms than for small firms. For the group of the 20% smaller firms in our sample, this result will appear only when we take cumulative returns of about one trimester

[2] Because we intended to work with a large sample, both in the cross section and in the time series, we could not use daily realized volatility computed from intraday returns, as for instance Scharth and Medeiros (2009). These authors also studied how the interaction between recent returns and cumulative returns over many days affects volatility. However, they worked with only 16 individual stocks from the Dow Jones Industrial Average over a period of ten years (form 1994 through 2003), because their focus was on the model to forecast volatility.

(approximately 64 trading days) a much longer period than the ten days used by ACG.

In summary, our results show that high frequency (daily) and low frequency (quarterly) returns contribute simultaneously to the asymmetric volatility effect. The major hypotheses to explain asymmetric volatility are the leverage effect, and volatility feedback, for which early references are Black (1976), and Pindyick (1984), respectively. The leverage effect hypothesis states that volatility increases after negative returns due to increase in financial leverage. ACG argue that daily shocks can not be associated to significant changes in leverage, and thus the leverage hypothesis can not explain asymmetric volatility at daily frequency. The volatility feedback hypothesis proposes that returns anticipate variations in volatility. Thus, risk averse investors will charge a premium to hold stocks when volatility (i.e. risk) is expected to increase. This premium reflects in price reductions (negative returns) preceding periods of higher volatility. However idiosyncratic risk should not be priced, because it can be diluted by forming a portfolio with many stocks in different industries. So, only changes in market volatility should be priced and these changes occur at the frequency of the business cycle.[3] Again, the hypothesis can not be associated to asymmetric volatility at daily frequency.

ACG found, as the results presented in this study, that asymmetric volatility is present at daily frequency. Additionally they show that daily asymmetric volatility is correlated with the share of sell trades (i.e. trades initiated by a sell offer). They recur to investors' behavioral biases to explain this result, arguing that herd behavior drives prices down and increase volatility, while informed purchases drive prices up and reduce volatility. However they argue that volatility should increase more when current return is negative and cumulative return is positive, which is at odds with our results. Conversely they argue that volatility should increase less when current return is positive and cumulative return is negative, which again is at odds with our results. We attribute this divergence to the fact that they evaluate the response of absolute returns to the product of current returns by the index of sell trades (i.e. the share of sell trades over total trades), while we evaluate the response to current returns. Also they

[3] A usual reference on the non pricing of idiosyncratic risk and the changes in risk in path with the business cycle is Cochrane (2005), Chapter One.

work only with cumulative returns over a period of ten days, and we show that results may change depending on the period taken to compute cumulative returns.

As ACG we rely on behavioral bias, particularly the "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. When cumulative return is positive, investors subject to disposition effect (henceforth DE investors) are willing to sell their stocks, and will coordinate sales in the presence of positive shocks to prices. If demand shocks cause price changes as in Campbell, Grossman and Wang (1993), then DE investors' sales will have a negative effect on prices, attenuating positive shocks to prices. In the case of positive cumulative return and positive current return, DE investors become more willing to sell, reducing the potential impact of positive shocks, and thus reducing expected volatility.

When cumulative return is negative, DE investors refuse to realize losses and keep the stock. Investors, especially professional ones, are aware that when riding a stock with negative cumulative return in their portfolios they may be driven by emotional resistance to realize losses. Thus, according to Shefrin and Statman (1985), investors develop self-control techniques, among which the most popular is the stop-loss threshold, which must be taken into account when analyzing the consequences of the disposition effect on the stock market. The triggering of stop-losses sales leads investors to coordinate sales when a stock presents negative cumulative return and is subject to a negative shock. Again, if demand shocks cause price changes as in Campbell, Grossman and Wang (1993), there is a negative impact on prices, amplifying the effect of negative shocks. So, with negative cumulative return and negative current return, stop-losses thresholds get closer, amplifying the potential impact of negative shocks, and thus increasing expected volatility.

Our results depend on the period over which cumulative return is computed. Because we refer to disposition effect as a source of asymmetric volatility, we propose the use of a measure of capital gain similar to the one proposed by Grinblatt and Han (2005) on a study about the relation between disposition effect and momentum.[4] When we combine the signs of current return and capital gain, instead of cumulative returns, 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.

Essential to our explanation for asymmetric volatility is the increase in the potential coordination of investors sales, either when cumulative and past return are positive, or when they are both negative. Indeed we do find that when cumulative and current returns have the same sign, volume is expected to increase in the following period, especially in the last two decades of our sample.

The rest of the article proceeds as follows. In the next section data used in the analyses is described. In section 3.3 we introduce the econometric model. In section 3.4 we present the results on how the combination of signs of current returns and cumulative returns affects asymmetric volatility. In section 3.5 we develop our explanation based on disposition effect and show the empirical analysis that supports it. Section 3.6 concludes.

3.2.
Data

We use the daily returns, shares outstanding and trading volumes from CRSP database over the period from January 1966 through December 2007. This period is split into four sub-perios: 1996-1976, 1977-1987, 1988-1998 and 1999-2007. 5 Data from 1965 is only used to estimate reference prices in a way similar to Grinblatt and Han (2005). Our sample comprises only common stocks listed at NYSE with data available for every trading day in each sub-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 procedure also removes firms that have gone through recent IPO, that have been delisted in the period, and that are illiquid. This enhances the focus on idiosyncratic volatility driven by exogenous demand shocks.

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

[5] The sample period that goes from January 1988 through December 1998 is the same period used by Avramov, Chordia and Goyal (2006).

Table 7 - Summary statistics by size group

Only common stocks listed at NYSE, with data for every trading day in the sample period are considered. Every trading day stocks are classified according to its market capitalization at the end of the day. Mean values over all observations (stock-dates) classified in the group are presented in the table, with corresponding standard deviations in parentheses; return is daily return, |return| is the absolute value of daily return, realized volatility is the volatility of daily returns over the 255 previous trading dates, turnover is the ratio of shares traded by the number of shares outstanding, and market capitalization is the product of price by shares outstanding. Because values for realized volatility and market capitalization are highly auto-correlated for each stock, standard deviations are not presented.

Panel A: 1999 – 2007 (1324 stocks and 2259 trading days)

Size Group	1 (small)	2	3	4	5 (big)
no. stocks	264	265	265	265	265
Return	0.030% (2.379%)	0.053% (2.399%)	0.066% (2.332%)	0.075% (2.223%)	0.065% (2.171%)
|return|	1.311% (1.985%)	1.465% (1.901%)	1.512% (1.777%)	1.478% (1.662%)	1.468% (1.602%)
Realized volatility	1.901%	2.080%	2.135%	2.079%	2.026%
Turnover	74.1% (272.0%)	114.8% (225.5%)	165.0% (246.7%)	177.9% (211.3%)	143.5% (149.5%)
Market capitalization	0.129	0.452	1.21	3.21	30.4

Panel B: 1988 – 1998 (844 stocks and 2799 trading days)

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

Table 7 - Summary statistics by size group (cont.)

Panel C: 1977 – 1987 (678 stocks and 2778 trading days)					
Size Group	1 (small)	2	3	4	5 (big)
no. stocks	135	136	135	136	136
Return	0.054% (2.927%)	0.070% (2.182%)	0.072% (2.006%)	0.067% (1.856%)	0.080% (1.759%)
|return|	1.809% (2.302%)	1.424% (1.655%)	1.336% (1.497%)	1.265% (1.361%)	1.221% (1.268%)
Realized volatility	2.574%	1.973%	1.822%	1.690%	1.598%
Turnover	49.0% (94.2%)	53.6% (130.5%)	53.9% (94.3%)	55.2% (88.7%)	54.4% (73.3%)
Market capitalization	0.056	0.200	0.490	1.08	4.56

Panel D: 1966 – 1976 (606 stocks and 2745 trading days)					
Size Group	1 (small)	2	3	4	5 (big)
no. stocks	121	121	121	121	122
Return	0.024% (2.852%)	0.047% (2.291%)	0.045% (2.124%)	0.045% (1.897%)	0.051% (1.714%)
|return|	1.877% (2.148%)	1.553% (1.684%)	1.465% (1.538%)	1.326% (1.357%)	1.214% (1.211%)
Realized volatility	2.659%	2.154%	2.006%	1.805%	1.639%
Turnover	36.7% (72.2%)	33.0% (62.0%)	31.8% (63.9%)	22.9% (37.0%)	18.5% (25.1%)
Market capitalization	0.040	0.113	0.254	0.544	2.31

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. The proxy for size was market capitalization computed as the product of share price by the number of shares outstanding on each date.[6] Summary statistics for

[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

each size group and each sub-period are presented in Table 7. Except for the number of stocks (which is fixed, despite the stocks in each group may change), values presented in Table 7 are mean values for respective variable, with standard deviation in parentheses, 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.

Interestingly mean return increases with mean market capitalization. This seems contradictory with the size anomaly, first reported by Banz (1981). However, we removed IPOs from our sample, which could probably be the small stocks with greater growth opportunities. Additionally we classified stocks based on daily market capitalization, and use returns contemporaneous to market capitalization when calculate mean returns, in Table 7. This implies that the figures in Table 7 may have been affected by "momentum effect", the tendency of past winners to continue presenting higher returns, and past losers to continue presenting lower returns, first described by Jegadeesh and Titman (1993). Winners will tend to have greater market capitalization, and losers, lower market capitalization. Due to "momentum effect", greater firms will concentrate winners, tending to present higher returns, and vice-versa. Besides, size effect seems to have disappeared, after controlling for risk, as, for instance, in Lewellen and Nagel (2006).[8]

The other variables in Table 7 behave as expected. Volatility decreases with size, as well as the mean absolute returns, which will be used as a proxy for volatility, except for the most recent sub-period (1999-2007). Mean realized volatility is greater than mean absolute return because more weight is put on extreme returns. Turnover increases with size, except for the quintile with greater firms, and except for the earlier sub-period (1966-1976). Yearly mean turnovers show expected magnitudes. Mean market capitalization presents an exponential pattern across groups sorted by size.

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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 the mean for each variable and then the mean of the variables in the size group.

[8] The sample used by Banz (1981) comprehended the period 1936 – 1975, while the Lewellen and

3.3. Econometric Model

Avramov, Chordia and Goyal (2006), 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 especially interested on how asymmetric volatility (the negative auto-correlation between volatility and lagged returns)[9] is affected by cumulative past returns. One approach to evaluate asymmetric volatility is estimating the parameters of the following regression:

$$\sigma^{p}_{j,t+1} = \alpha + \left(\theta_0 + \theta_1 I^{*}_{j,t}\right)\cdot\left|\varepsilon_{j,t}\right| + \sum_i \phi_i \sigma^{p}_{j,t-i} + v_{j,t} \tag{9}$$

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

Nagel (2006) used the period 1964 – 2001.

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

partial correlation between past returns and volatility.[10] The existence of asymmetric volatility effect is characterized by a statistically significant negative parameter θ_1.

We expand equation (9) to include the different dummies defined similarly to ACG:

$$\sigma^p_{j,t+1} = \alpha + \left(\theta_0 + \theta_1 I^{nn}_{j,t} + \theta_2 I^{pn}_{j,t} + \theta_3 I^{pp}_{j,t}\right)\cdot\left|\varepsilon_{j,t}\right| + \sum_i \phi_i \sigma^p_{j,t-i} + v_{j,t} \qquad (10)$$

where θ_2 and θ_3 are additional parameters to be estimated. As ACG did, past cumulative returns are calculated for the ten previous days. [11]

Also, to avoid the use of a large set of lags of volatility, we follow Corsi (2009) and use an additive cascade model. Corsi suggests the estimate of daily volatility using realized volatilities over the previous day, week and month. Because we are not working with intraday data (Corsi was), we can not calculate realized volatility at daily frequency. We, then, 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).[12] Thus, we will estimate volatility as:

$$\sigma^p_{j,t+1} = \alpha + \left(\theta_0 + \theta_1 I^{nn}_{j,t} + \theta_2 I^{pn}_{j,t} + \theta_3 I^{pp}_{j,t}\right)\cdot\left|\varepsilon_{j,t}\right| + \phi_1 RV^{22}_{j,t} + \phi_2 RV^{128}_{j,t} + v_{j,t} \qquad (11)$$

where $RV^D{}_{j,t}$ 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

evidence of asymmetric volatility in daily returns for individual stocks.

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

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

[12] Though we could compute realized weekly volatility (or volatility over the previous five days), this would be calculated using only five observations. This measure is too noisy. Indeed, when we introduce it in equation (11), the coefficients are not statistically significant. Corsi (2009) also noted that when working with the volatility of the T-Bond, which presents a lower mean tick arrival frequency (i.e. less observations per day) than the S&P (another series used by Corsi), “noisier estimation of the daily realized volatility induces a lack of significance of the daily volatility component”.

current return is negative, and $I^{pp}{}_{j,t} = 1$ if past cumulative return and current return are positive.

3.4. Results

We use absolute daily return as proxy for daily volatility in equation (11). We, then, will estimate the parameters for the following equation:

$$\left|r_{j,t+1}\right| = \alpha + \left(\theta_0 + \theta_1 I^{nn}_{j,t} + \theta_2 I^{pn}_{j,t} + \theta_3 I^{pp}_{j,t}\right)\cdot\left|r_{j,t}\right| + \\ + \frac{1}{22}\phi_1\sum_{i=0}^{21}\left|r_{j,t-i}\right| + \frac{1}{127}\phi_2\sum_{i=0}^{127}\left|r_{j,t-i}\right| + v_{j,t} \tag{12}$$

where j indexes stocks, t indexes trading days, r is daily return, I^{ss} are dummies, $v_{j,t}$ is an error term, and α, θ_0, θ_1, θ_2, θ_3, ϕ_1 and ϕ_2 are parameters to be estimated. The dummies I^{ss} are defined as follows: $I^{nn} = 1$ 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. Past cumulative returns are calculated over the ten days preceding t.

The absolute value of unexpected return has been used as a proxy for daily volatility at least since Schwert (1990), and has been used by ACG.[13] The use of a direct measure of volatility allows pooling data in our analyses. Because we are interested in performing analysis 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.[14] To keep consistency, we calculate realized volatility as the mean of absolute returns, instead of the mean of the squares of demeaned returns.

[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 practically impossible, mainly if we want to expand the analysis backward in time.

[14] When using pooled OLS to estimate mean parameters considering all stocks in the sample, to obtain consistent estimators it is only necessary independency between the error term $v_{j,t}$ and corresponding (i.e. with same j and t) explanatory variables. Correlation between contemporaneous variables is not a problem.

We run pooled OLS regressions with equation (12). Although we have a balanced panel data set, we do not run panel regressions with fixed effects.[15] There are three reasons for this. First, the asymptotic properties of linear panel data model are valid for large number of stocks and limited number of time periods. Clearly this is not the case: we have three times more dates than stocks. Second, due to the use of lags of absolute returns, the error terms $v_{i,t}$ are auto-correlated with the set of explanatory variables. Then we can not appropriately estimate the covariance matrix of the parameters in equation (12). Third, we do not need to control for fixed effects because the cascade terms account for differences of unconditional variance in the cross section of stocks.

Volatility is relevant because it is related to risk. Thus, it should consider only unexpected changes in asset prices. When we use simple daily returns as a proxy for daily volatility, and to calculate realized volatility, we are implicitly assuming that the series of daily prices is a martingale, that is, one can not predict returns. There is, however, 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 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.[16] 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 MacKinely, 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".[17] Indeed, mean expected return is much lower than the standard

[15] See Wooldridge (2002) for a review of linear panel data model (chapter 7) and fixed effects methods (chapter 10).

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

[17] 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 (2006). Indeed they allege to be following Schwert (1990), but this author was working with an aggregate market index (the CRSP value weighted index), for which auto-correlations are statistically and economically significant.

deviation of daily returns, as we see in Table 7. 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.

Table 8 presents the estimated parameters in equation (12). In parenthesis are *t* statistics using standard errors robust to heteorskedasticity. Coefficient θ_1 is highly statistically significant for all time periods, and for all number of days considered to compute cumulative return (except the period from 1966 through 1976, when cumulative return is computed over 64 days, approximately one quarter, or more). Coefficient θ_3 is positive and statistically significant when the number of days used to compute cumulative return is greater than 22 days (approximately one month).

Table 8 - Volatility and past returns: pooled regression

The dependent variable is absolute daily return. The table presents estimated parameters, and corresponding *t*-statistics adjusted for heteroskedasticity (in parenthesis), for the following regression:

$$\left|r_{j,t+1}\right| = \alpha + \left(\theta_0 + \theta_1 I_{j,t}^{nn} + \theta_2 I_{j,t}^{pn} + \theta_3 I_{j,t}^{pp}\right)\cdot\left|r_{j,t}\right| + \phi_1 \frac{1}{22}\sum_{i=0}^{21}\left|r_{j,t-i}\right| + \phi_2 \frac{1}{127}\sum_{i=0}^{127}\left|r_{j,t-i}\right| + v_{j,t}$$

where *j* indexes stocks, *t* indexes trading days, *r* is daily return, I^{ss} are dummies, $v_{j,t}$ is an error term, and α, θ_0, θ_1, θ_2, θ_3, ϕ_1 and ϕ_2 are parameters to be estimated. The dummies I^{ss} are defined as follows: I^{nn} = 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. Past cumulative returns are calculated over *D* days preceding *t*.

Panel A: 1999 – 2007 (1324 stocks and 2259 trading days)							
D (days)	1	5	10	22	64	128	255
θ_1	0.065 (19.50)	0.089 (26.67)	0.084 (26.53)	0.079 (22.54)	0.065 (17.95)	0.057 (14.34)	0.052 (12.43)
θ_2	0.024 (8.20)	0.001 (0.40)	-0.009 (-2.56)	-0.014 (-4.69)	-0.000 (-0.16)	0.011 (3.99)	0.019 (6.87)
θ_3	-0.007 (-2.51)	-0.005 (-1.66)	-0.021 (-7.67)	-0.031 (-11.63)	-0.037 (-13.84)	-0.035 (-13.10)	-0.033 (-12.37)
θ_0	0.105 (47.46)	0.101 (42.13)	0.108 (43.20)	0.113 (44.16)	0.116 (44.11)	0.116 (43.03)	0.116 (41.74)
ϕ_1	0.395 (94.39)	0.399 (95.37)	0.397 (94.92)	0.388 (92.85)	0.380 (89.99)	0.386 (92.38)	0.392 (93.79)
ϕ_2	0.409 (100.14)	0.407 (99.63)	0.410 (100.22)	0.418 (102.42)	0.422 (103.07)	0.412 (101.31)	0.405 (97.77)
α	0.001 (35.83)	0.001 (36.28)	0.001 (36.72)	0.001 (37.64)	0.001 (39.28)	0.001 (41.89)	0.001 (43.23)
R^2	19.62%	19.75%	19.77%	19.78%	19.71%	19.67%	19.65%

Table 8 - Volatility and past returns: pooled regression (cont.)

Panel B: 1988 – 1998 (844 stocks and 2799 trading days)

D (days)	1	5	10	22	64	128	255
θ_1	0.037 (9.22)	0.082 (15.67)	0.078 (6.98)	0.069 (12.87)	0.048 (10.60)	0.041 (7.27)	0.029 (4.75)
θ_2	-0.017 (-4.35)	-0.021 (-5.85)	-0.041 (-5.17)	-0.031 (-8.46)	-0.029 (-5.72)	-0.017 (-4.75)	-0.006 (-1.81)
θ_3	-0.013 (-3.44)	0.014 (3.98)	0.082 (6.98)	-0.011 (-3.11)	-0.029 (-8.40)	-0.025 (-7.22)	-0.028 (-7.84)
θ_0	0.123 (35.76)	0.107 (37.80)	0.124 (22.45)	0.118 (40.02)	0.127 (40.17)	0.126 (25.86)	0.128 (37.33)
ϕ_1	0.338 (63.09)	0.341 (63.16)	0.297 (27.45)	0.338 (62.64)	0.325 (60.14)	0.279 (25.27)	0.334 (61.23)
ϕ_2	0.461 (79.84)	0.462 (80.09)	0.512 (45.29)	0.461 (80.01)	0.469 (81.31)	0.521 (46.15	0.455 (78.57)
α	0.001 (20.21)	0.001 (19.12)	0.001 (9.30)	0.001 (20.62)	0.001 (22.07)	0.001 (11.51)	0.001 (23.60)
R^2	15.84%	15.83%	15.83%	15.83%	15.84%	17.20%	17.16%

Table 8 - Volatility and past returns: pooled regression (cont.)

Panel C: 1977 – 1987 (678 stocks and 2778 trading days)

D (days)	1	5	10	22	64	128	255
θ_1	0.071 (18.03)	0.089 (22.75)	0.086 (21.74)	0.078 (23.34)	0.061 (14.10)	0.041 (9.15)	0.022 (4.35)
θ_2	-0.015 (-4.55)	-0.039 (-13.15)	-0.043 (-14.96)	-0.042 (-14.41)	-0.026 (-8.60)	-0.009 (-2.82)	0.001 (0.23)
θ_3	-0.001 (-0.43)	0.006 (2.00)	-0.005 (-1.72)	-0.015 (-5.33)	-0.024 (-8.30)	-0.030 (-10.16)	-0.035 (-11.15)
θ_0	0.132 (59.64)	0.126 (50.45)	0.131 (53.08)	0.136 (54.42)	0.142 (53.76)	0.147 (54.54)	0.152 (48.43)
ϕ_1	0.295 (62.40)	0.302 (63.99)	0.303 (64.07)	0.297 (62.88)	0.286 (60.61)	0.288 (61.06)	0.292 (61.81)
ϕ_2	0.491 (83.89)	0.489 (83.46)	0.487 (83.02)	0.489 (83.45)	0.495 (84.82)	0.491 (83.98)	0.486 (82.69)
α	0.001 (21.80)	0.001 (21.80)	0.001 (22.50)	0.001 (23.34)	0.001 (24.16)	0.001 (24.30)	0.001 (24.67)
R^2	13.74%	13.92%	13.93%	13.89%	13.77%	13.69%	13.66%

Table 8 - Volatility and past returns: pooled regression (cont.)

Panel D: 1966 – 1976 (606 stocks and 2745 trading days)							
D (days)	1	5	10	22	64	128	255
θ_1	0.016 (5.24)	0.028 (9.53)	0.024 (7.95)	0.017 (5.83)	0.005 (1.69)	-0.003 (-0.95)	-0.005 (-1.59)
θ_2	-0.031 (-11.98)	-0.052 (-19.78)	-0.064 (-24.51)	-0.073 (-26.67)	-0.064 (-23.63)	-0.061 (-23.28)	-0.047 (-19.32)
θ_3	0.000 (0.09)	-0.002 (-0.96)	-0.019 (-7.99)	-0.036 (-14.77)	-0.042 (-17.26)	-0.049 (-20.38)	-0.038 (-16.05)
θ_0	0.111 (59.45)	0.112 (53.82)	0.120 (58.63)	0.127 (62.94)	0.131 (63.66)	0.134 (63.60)	0.130 (60.56)
ϕ_1	0.338 (75.92)	0.342 (77.12)	0.344 (77.45)	0.341 (76.78)	0.322 (72.09)	0.321 (71.94)	0.328 (73.74)
ϕ_2	0.458 (94.72)	0.457 (94.63)	0.456 (94.46)	0.460 (95.39)	0.476 (97.93)	0.472 (97.64)	0.459 (95.11)
α	0.001 (33.08)	0.001 (32.56)	0.001 (32.59)	0.001 (32.71)	0.001 (33.71)	0.002 (35.46)	0.002 (37.58)
R^2	12.90%	12.99%	13.02%	13.05%	13.00%	12.99%	12.93%

3.5.
An explanation

Our results show that high frequency (daily) and low frequency (quarterly) returns contribute simultaneously to the asymmetric volatility effect. Particularly, when current return and cumulative return are both negative, volatility tends to increase. Conversely, when current and cumulative returns are both negative, volatility tends to reduce. The main explanations to asymmetric volatility are the leverage effect, and volatility feedback, for which early references are Black (1976), and Pindyick (1984), respectively. However, both explanations are best fitted for returns and volatility measured at frequencies lower than daily.

Avramov, Chordia and Goyal (2006) also find asymmetric volatility for individual stocks at daily frequency, and show that it is driven by the share of sell trades over total trades. They explain this result based on behavioral biases, arguing that herd behavior drives prices down and increase volatility, while informed purchases drive prices up and reduce volatility. The main divergence between ours and ACG's explanation is about the combination of signs of cumulative and current returns that is related to greater and smaller increases in volatility. ACG find that the greater increase in volatility occurs for positive current return combined with negative cumulative return, while for us the greater increase is associated to both being negative. On the opposite side, ACG find that the smaller increase in volatility in response to price shocks occurs when current return is positive and cumulative return is negative, while for us smaller increase in volatility is associated to both being positive. We attribute this divergence to the fact that instead of using returns (i.e. price shocks) directly as explanatory variable, they used the product of daily return by an index of sell trades. That is, they run regressions using an equation similar to equation (12), bust instead of $|r_{j,t}|$ in the right side, they use $|r_{j,t}| \cdot (NS_{j,t} / NT_{j,t})$, where $NS_{j,t}$ and $NT_{j,t}$ are, respectively, the number sells and the total number of trades. Additionally ACG compute cumulative returns over the previous ten days. We have shown, however, that the response of volatility to the combination of signs of current and cumulative returns depends on the period over which cumulative returns are computed.

So, previous studies on the subject can not explain our results. To provide an explanation it is first necessary to understand what drives volatility. So, we define demand shocks and describe how they affect prices. We propose that price changes under demand shocks may be affected by a specific behavioral bias that has intensity linked to past returns. Finally we provide empirical evidence that supports our argument.

3.5.1.
Sources of volatility

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.

We will define demand shocks as price changes not related to public information, because we postulate that these price changes arise to accommodate trading initiated by private motivation. Demand may suffer a positive shock (increase) when private motivation leads investors to buy a stock, or a negative shock (decrease), when private motivation leads investors to sell a stock.[18] Although it seems that other investors could arbitrage on these price deviations, market frictions constrain arbitrage strategies. For instance, if there are investors with private information, there is a problem of adverse selection that limits arbitrage strategies against demand shocks.[19] 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. Even worse, noise traders may increase their bets, leading to negative returns for the arbitrageurs in the short run.[20] The impact of demand shocks on prices will depend on the risk assumed by those agents who absorb the demand shock. The greater is the volume, the greater is the risk.[21] If price changes are not related to news (either public or private), but to demand shocks, then they tend to be reversed, as shown by Campbell, Grossman and Wang (1993). This amplifies the contribution of demand shocks to volatility, because besides the price change due to the demand shock, there is the price change due to the reversal.[22]

[18] 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.

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

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

[21] In Kyle (1985), for instance, the greater the size of an order that an agent takes (in his case the “market maker”), the greater is the premium charged.

[22] We will again justify our preference for returns in equation (12), instead of unexpected returns taken as the residuals of an auto-correlation process. We are arguing, as Campbell, Grossman and Wang (1993), that part of the volatility arises from price adjustment after demand shocks. 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 inter-temporal relation between expected return and risk (standard deviation from expected returns).

3.5.2. Disposition effect, self control, and their effect on volatility

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.[23] Odean (1988) provides empirical evidence that many individual 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.[24]

In the presence of investors subject to disposition effect (henceforth DE investors) DE investors are inclined to sell their shares when they are gaining on a stock. (That is, when the stock presents positive cumulative return.) If there is an exogenous shock that would move the price of a stock up, the coordinated selling by DE investors will be a demand shock in the opposite direction, attenuating positive impacts on prices. That is, under positive cumulative return and positive current return, the impact of positive shocks is attenuated, as well as its eventual reversal. That is, the expected value of absolute returns (our proxy for volatility) is lower.

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[23] The disposition effect 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 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).

[24] Indeed, Grinblatt and Han (2005) develop an equilibrium model based on 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.

Conversely, when the stock presents negative cumulative return, that is, when DE investors are losing on a stock, they tend to hold the stock, to avoid realizing a loss. Shefrin and Statman (1985) argue that investors may be aware of this emotional factor and develop self control techniques that must be considered when analyzing the effect of disposition effect on the stock market. A largely applied self control technique is the determination of a loss limit. If cumulative return is sufficiently negative to impose the loss limit to the investor, he immediately (or eventually automatically) sends a sell order at market price. This "stop-losses" technique coordinates sells when prices are falling, increasing the impact of negative shocks, as well as its eventual reversal. So under negative cumulative return and negative current return, the expected value of absolute returns is greater.

3.5.3.
Capital gain as a representative computation of cumulative return

The problem with the argument above is that the sign of coefficient θ_3 in equation (12) should be negative, but in Table 8 we see that this sign is ambiguous if cumulative return is computed for periods lower than 22 trading days (approximately one month). What is the best representative period to compute cumulative returns?

Core to the disposition effect 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.[25] 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 255 days (approximately 1 year) backwards.[26] The weights are proxies for the quantity of shares that DE investors bought on date *t–k*, and still hold on date *t*, normalized

[25] Note that because dividends are not considered, capital gain over a period is usually not the same as the return.

[26] 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.

so that the sum of weights equals one.[27] Following this procedure, capital gain, labeled g_t, is computed as:

$$g_{j,t} = \sum_{k=1}^{250} w_{j,t-k} \left[\prod_{n=0}^{k-1} \left(1 + r^*_{j,t-k}\right) - 1 \right] \tag{13a}$$

$$w_{j,t} = \frac{V_{j,t-k} \prod_{i=0}^{k-1} \left(1 - V_{j,t-i}\right)}{\sum_{k=1}^{250} \left[V_{j,t-k} \prod_{i=0}^{k-1} \left(1 - V_{j,t-i}\right) \right]} \tag{13b}$$

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.[28]

Table 9 presents the estimated parameters in equation (12), 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 D days. The main difference between Table 8 and Table 9 is that in the second the sign of θ_3 is not ambiguous anymore, even splitting the sample for each time period by size quintiles. Indeed, as expected from our argument, it is negative and statistically significant at 1% level for four out of five size groups, for each time period, and at 10% level for all size groups and time periods. We also notice that θ_1 is negative only for small firms in the period from 1966 through 1976, what may be a bias due to size. Coefficient θ_2, which plays no role in our argument, presents ambiguous sign in Table 9, and is usually non statistically significant. These evidences are all consistent with our argument that cumulative return plays a role in the forecast of stock prices volatility, mainly when its sign is the same of current return.

[27] Actually, because we do not know what part of trading volume is due to DE investors, the capital gain is calculated for an average investor and attributed to DE investor.

[28] 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.

Table 9 –
Volatility and capital gain (intensity of disposition effect): pooled regression

The dependent variable is absolute daily return. The table presents estimated parameters, and corresponding *t*-statistics adjusted for heteroskedasticity (in parenthesis), for the following regression:

$$\left|r_{j,t+1}\right| = \alpha + \left(\theta_0 + \theta_1 I^{nn}_{j,t} + \theta_2 I^{pn}_{j,t} + \theta_3 I^{pp}_{j,t}\right)\cdot\left|r_{j,t}\right| + \phi_1 \frac{1}{22}\sum_{i=0}^{21}\left|r_{j,t-i}\right| + \phi_2 \frac{1}{127}\sum_{i=0}^{127}\left|r_{j,t-i}\right| + v_{j,t}$$

where *j* indexes stocks, *t* indexes trading days, *r* is daily return, I^{ss} are dummies, $v_{j,t}$ is an error term, and α, θ_0, θ_1, θ_2, θ_3, ϕ_1 and ϕ_2 are parameters to be estimated. The dummies I^{ss} are defined as follows: I^{nn} = 1 if capital gain $g_{j,t}$ and current return are negative; $I^{pn}_{j,t}$ = 1 if capital gain $g_{j,t}$ is positive and current return is negative, and $I^{pp}_{j,t}$ = 1 if capital gain $g_{j,t}$ and current return are positive. Capital gain $g_{j,t}$ is calculated according to equations (13a) and (13b) in a procedure similar to the one proposed by Grinblatt and Han (2005).

Panel A: 1999 – 2007 (1324 stocks and 2259 trading days)

Size Group	5 (big)	4	3	2	1 (small)
θ_1	0.064	0.072	0.051	0.059	0.079
	(11.42)	(10.31)	(7.58)	(8.81)	(6.53)
θ_2	0.001	-0.007	0.001	0.003	0.002
	(0.29)	(-1.70)	(0.21)	(0.57)	(0.21)
θ_3	-0.053	-0.047	-0.041	-0.037	-0.016
	(-13.85)	(-10.67)	(-8.74)	(-7.57)	(-1.76)
θ_0	0.077	0.099	0.112	0.128	0.154
	(21.13)	(26.60)	(26.26)	(28.14)	(18.09)
ϕ_1	0.427	0.402	0.373	0.367	0.359
	(59.50)	(46.06)	(44.49)	(46.68)	(31.37)
ϕ_2	0.405	0.396	0.417	0.429	0.419
	(55.88)	(46.95)	(49.42)	(54.48)	(38.15)
α	0.002	0.002	0.001	0.001	0.001
	(23.11)	(23.94)	(21.66)	(21.93)	(12.34)
R^2	17.29%	16.24%	16.71%	20.82%	24.98%

Panel B: 1988 – 1998 (844 stocks and 2799 trading days)

Size Group	5 (big)	4	3	2	1 (small)
θ_1	0.050	0.054	0.042	0.055	0.037
	(8.44)	(9.33)	(6.63)	(7.30)	(3.49)
θ_2	0.021	0.009	0.003	-0.011	-0.059
	(4.87)	(2.02)	(0.51)	(-2.03)	(-7.57)
θ_3	-0.026	-0.033	-0.020	-0.009	-0.026
	(-6.68)	(-8.11)	(-4.35)	(-1.71)	(-3.43)
θ_0	0.090	0.108	0.108	0.112	0.145
	(23.58)	(28.82)	(25.21)	(24.52)	(25.64)
ϕ_1	0.406	0.377	0.363	0.336	0.282
	(55.74)	(50.10)	(42.78)	(38.91)	(25.65)
ϕ_2	0.332	0.371	0.412	0.428	0.521
	(43.32)	(47.44)	(47.01)	(44.83)	(46.20)
α	0.002	0.002	0.001	0.002	0.001
	(32.21)	(27.62)	(22.51)	(21.27)	(11.00)
R^2	9.38%	11.49%	13.29%	14.35%	19.47%

Table 9 (cont.) –
Volatility and capital gain (intensity of disposition effect): pooled regression

Panel C: 1977 – 1987 (678 stocks and 2778 trading days)					
Size Group	5 (big)	4	3	2	1 (small)
θ_1	0.051 (5.13)	0.042 (5.11)	0.067 (8.28)	0.059 (7.14)	0.041 (4.77)
θ_2	-0.012 (-1.81)	-0.007 (-1.04)	0.004 (0.68)	-0.006 (-0.98)	-0.043 (-6.83)
θ_3	-0.037 (-7.50)	-0.033 (-6.44)	-0.032 (-6.55)	-0.010 (-1.71)	-0.023 (-3.81)
θ_0	0.141 (27.74)	0.140 (26.70)	0.138 (30.96)	0.147 (30.18)	0.146 (28.53)
ϕ_1	0.316 (36.49)	0.289 (32.31)	0.312 (34.27)	0.283 (30.10)	0.271 (26.57)
ϕ_2	0.448 (45.14)	0.476 (47.85)	0.439 (42.98)	0.471 (42.89)	0.518 (41.68)
α	0.001 (19.39)	0.001 (19.25)	0.002 (19.65)	0.001 (16.91)	0.001 (11.11)
R^2	10.19%	51.67%	11.37%	12.96%	13.63%
Panel D: 1966 – 1976 (606 stocks and 2745 trading days)					
Size Group	5 (big)	4	3	2	1 (small)
θ_1	0.009 (1.71)	0.011 (2.05)	0.017 (3.02)	-0.009 (-1.83)	-0.014 (-2.14)
θ_2	-0.040 (-9.16)	-0.049 (-10.17)	-0.048 (-10.06)	-0.067 (-13.13)	-0.088 (-13.24)
θ_3	-0.053 (-12.54)	-0.062 (-13.07)	-0.044 (-9.68)	-0.049 (-10.12)	-0.039 (-7.31)
θ_0	0.117 (31.98)	0.132 (31.57)	0.120 (31.58)	0.133 (31.90)	0.141 (33.83)
ϕ_1	0.378 (46.11)	0.337 (39.39)	0.333 (39.01)	0.318 (36.61)	0.289 (28.98)
ϕ_2	0.382 (41.46)	0.419 (43.82)	0.453 (46.88)	0.463 (48.11)	0.496 (45.71)
α	0.002 (23.87)	0.002 (23.46)	0.002 (19.50)	0.002 (21.26)	0.002 (16.25)
R^2	10.65%	10.93%	11.47%	11.78%	11.26%

3.5.4.
An empirical test

In our explanation, when capital gain and current return have the same sign, the potential coordination of sell trades by DE investors increase. This is consistent with the finding by Avramov, Chordia and Goyal (2006) that asymmetric volatility is driven by sell trades. If this source of trades is independent of other sources of trades, expected trading volume should increase when the signs of capital gain and current return are the same. So, if our explanation holds, the signs of parameters γ_1 and γ_3 should be positive in equation (14) below:

$$s_{j,t+1} = \beta_0 s_{j,t} + \beta_1 \frac{1}{22}\sum_{i=1}^{22} s_{j,t-i} + \beta_2 \frac{1}{64}\sum_{i=1}^{64} s_{j,t-i} + \beta_3 \frac{1}{128}\sum_{i=1}^{128} s_{j,t-i} + \\ + \delta\left|r_{j,t+1}\right| + \left(\gamma_0 + \gamma_1 I_{j,t}^{nn} + \gamma_3 I_{j,t}^{pp}\right) + u_{j,t+1} \tag{14}$$

where $r_{j,t}$ is the daily return of stock j, $u_{j,t}$ is an error term, and $s_{j,t}$ is the daily turnover of stock j normalized through the division by the mean daily turnover for the past 255 days (approximately one year). Daily turnover is measured as the ratio of shares traded on a day over outstanding shares. Parameters β_0, β_1, β_2, δ, γ_0, γ_1, γ_2 and γ_3 are determined by an OLS regression. The the dummies $I^{nn}{}_{j,t}$, $I^{pn}{}_{j,t}$ and $I^{pp}{}_{j,t}$, are defined as before, so that: $I^{nn}{}_{j,t} = 1$ if capital gain $g_{j,t}$ and current return are negative; $I^{pn}{}_{j,t} = 1$ if capital gain $g_{j,t}$ is positive and current return is negative, and $I^{pp}{}_{j,t} = 1$ if capital gain $g_{j,t}$ and current return are positive. Capital gain $g_{j,t}$ is calculated according to equations (13a) and (13b) in a procedure similar to the one proposed by Grinblatt and Han (2005).

Note that we must control for absolute returns, because of the well known stylized fact that volume and absolute returns are positively correlated, as reported, for instance, by Karpoff (1987). Otherwise parameter γ_1, could be positive as a consequence of this correlation. The mean volume over one month (22 trading days), one quarter (64 trading days) and one semester (128 trading days) incorporate the increasing trend in turnover across over time, as can be noted in Table 7, and account for the long term dependence in turnover, as made for absolute returns in equation (12), following Corsi (2009).

Consistent with our explanation, Table 10 shows that parameter γ_3 is positive and statistically significant at 1% level, in equation (14), for all time periods and size groups. The parameter γ_1 is positive and statistically significant for most size groups, in the most recent time periods, of 1999-2007 and 1988-

1998. For the only case when γ_1 is negative, in these time periods, it is not statistically significant. However, for the earlier time periods 1966-1976 and 1977-1987 when coefficient γ_1 is statistically significant, it is negative. Previously, we noticed that in Table 8 and Table 9 the period 1966-1976 was also an exception for the coefficient θ_1 associated with negative current return and negative cumulative return. One possibility is that during that period self control techniques, such as stop-losses sell orders, were not well developed.

Table 10 - Turnover and capital gain (intensity of disposition effect): pooled regression

The dependent variable is daily turnover, measured as the ratio of shares traded on a day over outstanding shares. The table presents estimated parameters, and corresponding *t*-statistics adjusted for heteroskedasticity (in parenthesis), for the following regression:

$$s_{j,t+1} = \beta_0 s_{j,t} + \beta_1 \frac{1}{22}\sum_{i=1}^{22} s_{j,t-i} + \beta_2 \frac{1}{64}\sum_{i=1}^{64} s_{j,t-i} + \beta_3 \frac{1}{128}\sum_{i=1}^{128} s_{j,t-i} + \delta \left| r_{j,t+1} \right| + \left(\gamma_0 + \gamma_1 I_{j,t}^{nn} + \gamma_3 I_{j,t}^{pp} \right) + u$$

where $r_{j,t}$ is the daily return of stock *j*, $u_{j,t}$ is an error term, and $s_{j,t}$ is the daily turnover of stock *j* normalized through the division by the mean daily turnover for the past 255 days (approximately one year). Daily turnover is measured as the ratio of shares traded on a day over outstanding shares. Parameters β_0, β_1, β_2, δ, γ_0, γ_1, γ_2 and γ_3 are determined by an OLS regression. The the dummies $I^{nn}_{j,t}$, $I^{pn}_{j,t}$ and $I^{pp}_{j,t}$, are defined as follows: $I^{nn}_{j,t}$ = 1 if capital gain $g_{j,t}$ and current return are negative; $I^{pn}_{j,t}$ = 1 if capital gain $g_{j,t}$ is positive and current return is negative, and $I^{pp}_{j,t}$ = 1 if capital gain $g_{j,t}$ and current return are positive. Capital gain $g_{j,t}$ is calculated according to equations (13a) and (13b) in a procedure similar to the one proposed by Grinblatt and Han (2005).

Panel A: 1999 – 2007 (1324 stocks and 2259 trading days)					
Size Group	5 (big)	4	3	2	1 (small)
γ_1	**0.046** **(7.50)**	**0.038** **(2.85)**	**0.030** **(3.04)**	**0.005** **(0.41)**	**0.034** **(1.34)**
γ_3	0.041 (9.34)	0.063 (5.88)	0.111 (13.6)	0.134 (11.59)	0.237 (9.42)
γ_0	-0.265 (-9.55)	-0.355 (-6.82)	-0.424 (-9.71)	-0.386 (-9.25)	-0.329 (-4.38)
β_0	0.374 (26.44)	0.323 (4.01)	0.381 (19.14)	0.317 (13.24)	0.287 (7.13)
β_1	0.373 (28.88)	0.352 (6.16)	0.461 (16.52)	0.422 (20.95)	0.459 (10.73)
β_2	0.144 (12.17)	0.239 (4.66)	0.070 (2.08)	0.198 (7.58)	0.090 (2.30)
β_3	0.104 (5.35)	0.134 (2.61)	0.054 (1.71)	0.094 (3.13)	0.205 (3.99)
δ	35.6 (49.77)	39.6 (40.96)	39.9 (27.94)	39.5 (41.32)	40.9 (19.24)
R^2	41.09%	29.9%	45.8%	34.1%	22.3%

Table 10 (cont.) –
Turnover and capital gain (intensity of disposition effect): pooled regression

Panel B: 1988 – 1998 (844 stocks and 2799 trading days)					
Size Group	5 (big)	4	3	2	1 (small)
γ_1	0.063 (5.26)	0.058 (3.90)	-0.021 (-1.41)	0.019 (0.99)	0.133 (2.19)
γ_3	0.060 (3.38)	0.061 (7.62)	0.136 (5.67)	0.227 (11.58)	0.473 (4.42)
γ_0	-0.074 (-1.72)	-0.144 (-6.45)	0.007 (0.14)	-0.369 (-7.33)	-0.874 (-1.54)
β_0	0.215 (13.97)	0.252 (21.67)	0.233 (5.31)	0.239 (11.04)	0.140 (1.92)
β_1	0.330 (23.15)	0.339 (22.28)	0.295 (8.40)	0.422 (14.07)	0.610 (4.10)
β_2	0.296 (13.25)	0.220 (14.30)	0.236 (7.43)	0.219 (6.33)	0.375 (1.47)
β_3	0.127 (5.21)	0.175 (8.50)	0.104 (2.60)	0.103 (2.88)	0.112 (0.19)
δ	38.3 (50.14)	40.9 (49.77)	43.3 (42.05)	48.7 (39.49)	38.6 (17.86)
R^2	3.79%	17.68%	14.07%	21.42%	26.11%

Panel C: 1977 – 1987 (678 stocks and 2778 trading days)					
Size Group	5 (big)	4	3	2	1 (small)
γ_1	0.002 (0.21)	-0.018 (-1.48)	-0.071 (-4.67)	-0.054 (-3.17)	-0.081 (-5.46)
γ_3	0.181 (12.38)	0.185 (16.96)	0.280 (17.27)	0.384 (17.80)	0.693 (27.82)
γ_0	-0.126 (-6.52)	-0.189 (-8.60)	-0.223 (-7.86)	-0.364 (-8.62)	-0.475 (-18.66)
β_0	0.213 (5.59)	0.221 (23.38)	0.178 (9.63)	0.192 (12.30)	0.253 (21.17)
β_1	0.413 (15.60)	0.417 (32.00)	0.429 (28.09)	0.441 (24.94)	0.412 (37.92)
β_2	0.175 (11.42)	0.167 (11.51)	0.193 (11.08)	0.158 (6.96)	0.114 (9.81)
β_3	0.204 (11.27)	0.247 (14.24)	0.197 (9.17)	0.197 (8.29)	0.208 (11.45)
δ	37.0 (51.21)	37.2 (49.04)	43.3 (43.57)	49.2 (38.09)	43.5 (54.71)
R^2	18.4%	17.9%	15.4%	17.3%	24.6%

Table 10 –
Turnover and capital gain (intensity of disposition effect): pooled regression (cont.)

Panel D: 1966 – 1976 (606 stocks and 2745 trading days)					
Size Group	5 (big)	4	3	2	1 (small)
γ_1	0.027 (2.70)	-0.005 (-0.38)	-0.082 (-5.36)	-0.044 (-2.81)	-0.056 (-3.45)
γ_3	0.157 (17.93)	0.285 (16.65)	0.328 (15.13)	0.518 (23.00)	0.836 (25.33)
γ_0	-0.120 (-7.35)	-0.118 (-3.26)	-0.161 (0.26)	-0.432 (-11.47)	-0.519 (-15.91)
β_0	0.195 (17.55)	0.108 (4.29)	0.223 (8.11)	0.203 (11.34)	0.254 (15.17)
β_1	0.480 (51.91)	0.519 (13.52)	0.435 (11.88)	0.466 (25.66)	0.440 (27.40)
β_2	0.194 (17.55)	0.179 (13.95)	0.153 (4.39)	0.152 (6.81)	0.160 (10.92)
β_3	0.109 (8.35)	0.171 (4.83)	0.105 (5.59)	0.139 (5.45)	0.073 (4.19)
δ	33.3 (55.29)	33.3 (51.75)	37.5 (42.01)	46.0 (35.06)	42.3 (51.39)
R^2	19.6%	12.9%	18.0%	20.6%	26.9%

Finally we should make the point that our result is not inconsistent with the results obtained by ACG. We recall that instead of using returns (i.e. price shocks) directly as explanatory variable, they used the product of daily return by an index of sell trades. The divergence stems from the fact that the index of sell trades is negatively correlated with returns, as reported by ACG. This means that when the shock (current return) is more negative, the sell trade index is greater, reducing the coefficient of the response of absolute returns to current returns. (Actually, by our explanation it is the greater sell trade index that amplifies the intensity of negative shocks.) Since the coefficients in our regressions do not account for the sell trade index, they are not reduced for negative current return, and we obtain the larger increase in volatility when current and cumulative returns are both negative. Analogously, when the shock is more positive, but cumulative return is negative, sell trade index is smaller. (The causality order based on our explanation is that when sell trades do not increase in the presence of positive shocks, because cumulative return is not positive, then positive shocks are not attenuated.) This increases the coefficient of the response of absolute returns in ACG's regressions.

3.6. 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 and current return are both negative. Conversely, volatility is expected to respond less intensively to price shocks when cumulative return and current return are both positive.

We explained this result as a consequence of the behavioral bias labeled "disposition effect" by Shefrin and Statman (1985). 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). To avoid incurring in large losses due to this propensity to hold stocks with negative capital gain, DE investors develop self-control techniques, as stop-loss limits. In our argument the potential that DE investors coordinate selling orders increase when cumulative and current return have the same sign. Their selling has negative impact on prices as in Campbell, Grossman and Wang (1993). This reduces the intensity of price changes and its eventual reversal, when cumulative and current returns are positive. This also increases the intensity of negative price changes and its eventual reversal, when cumulative and current returns are negative.

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, to obtain a representative value for cumulative return, instead of arbitrarily choosing a period to compute it, we confirm that volatility increases more in the presence of capital loss and negative current return, and increases less in the presence of positive capital gain and positive current return.

Core to our explanation is the coordination of selling when capital gain and current return have the same sign. So we should expect that trading volume should increase under both conditions. We present empirical evidence that this is the case, at least for the last two decades. This evidence supports our explanation, based on disposition effect, for the relevance of past returns on asymmetric volatility.