# MENTAL FRAMING IN RISK-AVERSION DYNAMICS
# AN EMPIRICAL INVESTIGATION OF INTERTEMPORAL CHOICE

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**KEYWORDS**

Asymmetric volatility; Risk seeking; Prospect theory; TGARCH; Volatility dynamics

**ABSTRACT**

This paper provides an empirical investigation of the mental framing based explanation for heteroscedasticity by Ormos and Timotity. We find empirical support for their model from two different point of view: first, the analysis of a huge individual trading dataset shows that investors indeed become risk-seeking right after losses and more risk-averse subsequent to gains; second, the parameter estimation of our volatility model yields the predicted negative relationship between abnormal returns and subsequent volatility.

## INTRODUCTION

Time-varying volatility (heteroscedasticity) of asset returns has attracted much research in the recent decades. Since the milestone papers of Engle (1982) and Bollerslev (1986) a great number of scholarly paper has been devoted to the topic. Their findings indicate that the phenomenon can be modeled by GARCH type models; however, an important aspect of the autoregression puzzle, the asymmetry in the volatility process still misses a robust explanation with empirical investigation. We aim to fill this void in the literature by providing empirical results for the theoretical model of Ormos and Timotity (2015), henceforth OT.

First, we show that, in line with results of Thaler and Johnson (1990), investors become risk-seeking following losses and risk-averse subsequent to gains if the opportunity of breaking-even is included in the choice set, which, in fact, almost always applies to asset returns. According to the model of OT, this pattern is due to the intertemporal mental framing of investors, which causes a negative relationship between previous unanticipated outcomes and risk-seeking. We confirm their hypothesis by analysing a large dataset containing individual trades and portfolio allocations.

Second, we present that the individually measured patterns of risk-aversion apply at the market level as well. Here, we find empirical support for the proposed theoretical volatility model of OT and confirm the existence of a negative relationship between previous market shocks and subsequent asset price volatility.

The paper is structured as follows: in section 2.1 the patterns in investors' intertemporal choice are discussed, then in 2.2 the volatility model is estimated. Finally, in section 3 we provide a brief conclusion on the main results.

## EMPIRICAL RESULTS

In this section we present our empirical results supporting the theoretical model of OT in two different ways: first, investors' dynamic behavior is tested on a large sample containing individual trading data; second, an empirical parameter estimation of our volatility model is provided using CRSP database consisting of the daily log-returns of the Standard and Poor's 500 index member listed on 10 September, 2014. The analysed period covers 21 years from 10 September 1993 to 10 September 2014.

### Patterns in intertemporal choice

We empirically investigate whether losses and gains induce risk-seeking and more risk-averse behavior respectively. As OT's theoretical model argue, this behavior is a response to loss-aversion in a dynamic context, that is, investors are reluctant to realize losses (either physically or mentally) and try to break even in order to obtain their initial benchmark on average. According to equilibrium asset pricing, higher required return that compensates for the previous loss can only be reached by investing in assets with increased risk; therefore, combined with the change in risk attitude, losses increase the volatility of returns in the subsequent period. Gains follow the opposite pattern: investors fear of losing the previous wealth, hence, they invest into less risky portfolios since the initial benchmark level is still reachable with the latter.

The data and methodology of this analysis are as follows: Our sample is similar to that of Barber and Odean (2000) consisting of the transactions and descriptive data of 158,006 accounts at a large discount brokerage firm from January 1991 to December 1996. In this paper we aim at defining the change in the riskiness (as measured by volatility) of investors' portfolio; therefore, only common stocks investments are considered, since a meaningful amount of historical returns and realized volatility can only be calculated for these assets. Nevertheless, findings in this reduced sub-

Proceedings 30th European Conference on Modelling and Simulation ©ECMS Thorsten Claus, Frank Herrmann, Michael Manitz, Oliver Rose (Editors)
ISBN: 978-0-9932440-2-5 / ISBN: 978-0-9932440-3-2 (CD)

sample should be representative for the whole sample as the former account for 64% of the latter as measured by the number of observations. Altogether, the dataset containing at least one common stock transaction in the period includes 104,225 accounts, which can be further decomposed based on the type of the account, in which we apply cash, IRA and margin accounts as control variables, and the equity held by the related household at the end of the period. In Table 1 the descriptive statistics of these sub-samples are presented.

Table 1: Descriptive statistics of the sample

| | All accounts | Cash accounts | IRA accounts | Margin accounts |
|---|---|---|---|---|
| **Num. of accounts** | 104,225 | 22,995 | 37,155 | 10,328 |
| **Mean equity** | 68,293 | 39,859 | 48,988 | 47,953 |
| **Median equity** | 18,288 | 8,419 | 21,549 | 4,426 |
| **St. dev. of equity** | 300,450 | 129,257 | 129,017 | 247,607 |
| **Num. of trades** | 1,969,747 | 260,039 | 486,889 | 255,759 |
| **Mean number of trades** | 19 | 11 | 13 | 25 |

Notes: The table shows the descriptive statistics of the trading accounts included in our dataset.

In return calculations we use different types of mental frames. First, we assume that when selling occurs the profit is measured as the selling price relative to the pre-transaction average buy price of an asset. However, as the long position in an asset may include numerous buy transactions before selling the stock, we argue that if the representativity or anchoring heuristics are responsible for the change in the risk attitude, the most recent information (i.e. the price of the last buy transaction) is the main factor in utility perception. Having calculated the gain or loss, the asset into which the realized money flows in the subsequent buy transaction is defined. Related to both the bought and sold assets the variance and standard deviation of daily returns in the preceding year are calculated. Finally, based on the aforementioned parameters, regressions are estimated to analyse whether the risk of the targeted asset is driven by the previous outcome.

As the number of trades of separate investors is often too small to caputre indivudal account effects, we apply a pooled data structure. Furthermore, since the number of accounts and trade numbers justify the use of the central limit theorem, our regressions are based on OLS estimations.

The first regression (first 2 columns in Table 2) applies a simple estimation of the variance of the targeted asset including the profit (the return based on the average buy price) of the previous transaction as the independent variable, that is

$$\sigma_{b,i}{}^2 = \hat{\alpha} + \widehat{\beta_1}\bar{r}_{s,i} + e_i, \qquad (1)$$

where $\sigma_{b,i}{}^2$ and $\bar{r}_{s,i,}$ stand for the variance of the asset in the subsequent buy transaction and the average return of the realized sell transaction of each $i$ trade pair respectively.

In the second regression we test whether the change in the definition of the return increases significance and goodness-of-fit. This estimation is shown in Eq. (2) where the previous profit $r_{s,i}$ is measured as the return on the price of the last transaction.

$$\sigma_{b,i}{}^2 = \hat{\alpha} + \widehat{\beta_1}r_{s,i} + e_i, \qquad (2)$$

One may argue that the variance also correlates with the risk of the sold asset as well: an investor may have a preference for risky assets, which could lead to a biased estimation of $\widehat{\beta_1}$ in the previous equation. Therefore, the third regression (Eq. (3)) includes $\sigma_{s,i}{}^2$ as the variance of the sold asset using the return on the last buy price respectively.

$$\sigma_{b,i}{}^2 = \hat{\alpha} + \widehat{\beta_1}r_{s,i} + \widehat{\beta_2}\sigma_{s,i}{}^2 + e_i, \qquad (3)$$

According to equilibrium pricing, investors do require a premium for risk; thus, their expected return is different from zero. Including this finding in the fourth regression, a new definition of return may provide a better fit to utility perception: here the perceived return is defined as the deviation from the historical (one year) expected return at the last buy transaction preceding the sell transaction of an asset. In other words, we assume that investors form their non-zero expectations at the time they invest into an asset based on its performance in the past. Accordingly, as both the length of time between last buy and subsequent sell transactions and the risk of assets varies throughout the data, another adjustment is required: the expected return is not the same for each transaction, hence, we standardize the deviation from the expected return by dividing it by the number of days between the buy and sell transactions. Subsequent to this definition we use this daily average deviation from the expectation as an independent variable as in the following Eq. (4), where $t_s$ and $t_{pb}$ stand for the time when the sell and the previous buy transactions occurred:

$$\sigma_{b,i}{}^2 = \hat{\alpha} + \widehat{\beta_1}r_{std,s,i} + \widehat{\beta_2}\sigma_{s,i}{}^2 + e_i : r_{std,s,i} = \\ = \frac{r_{s,i} - E(r_i|t=t_{pb})}{t_s - t_{pb}} \qquad (4)$$

In order to be able to distinguish effects of previous gains from losses we apply two separated variables in regression five as defined in Eq. (5):

$$\sigma_{b,i}{}^2 = \hat{\alpha} + \widehat{\beta_1}r_{-std,s,i} + \widehat{\beta_2}r_{+std,s,i} + \widehat{\beta_3}\sigma_{s,i}{}^2 + e_i : \\ r_{-std,s,i} = \min(r_{std,s,i}, 0), r_{+std,s,i} = \max(r_{std,s,i}, 0) \qquad (5)$$

Having analysed the effects of previous outcomes on risk attitude as measured by variance, we provide further tests that include volatility instead of the former. The importance of this additional analysis is already highlighted, where we discussed that asset prices in prospect theory are driven by standard deviation rather than variance. Hence, in further regressions we apply volatility as the dependent variable. The sixth regression

is the same as Eq. (5) except for the previously defined change in the definition of risk.

Our extensive dataset covers further parameters related to each trading account; in particular, the equity held at the end of the period and the type of the account is included as well. In further regressions we also apply these latter measures as control variables and investigate differences between the subgroups. The seventh regression is defined as in Eq. (6), where $E_i, D_{C,i}, D_{I,i}$ and $D_{M,i}$ stand for the equity, the cash type dummy, the IRA type dummy and the margin dummy of the account related to the $i^{th}$ transaction respectively.

$$\sigma_{b,i} = \hat{\alpha} + \widehat{\beta_1} r_{std,s,i} + \widehat{\beta_2}\sigma_{s,i} + \widehat{\beta_3} E_i + \widehat{\beta_4} D_{C,i} + \\ + \widehat{\beta_5} D_{I,i} + \widehat{\beta_6} D_{M,i} + e_i \qquad (6)$$

In regression eight we modify Eq. (6) according to Eq. (5), that is, by separately estimating the coefficients of gains and losses. Then, in subsequent estimations we apply this latter frame in subgroup estimations: in the ninth equation the effects for accounts with equity value above its median (i.e. the top 50% of investors ranked by equity value) are estimated, whereas the tenth calculates coefficients for the bottom 50%. In the last three regressions effects for subgroups with a cash, IRA and margin account types are estimated.

Table 2: Regression results

**Panel A**

| | Subsequent $\sigma^2$ (Eq. 1) | | Subsequent $\sigma^2$ (Eq. 2) | | Subsequent $\sigma^2$ (Eq. 3) | |
|---|---|---|---|---|---|---|
| | Coef | p-value | Coef | p-value | Coef | p-value |
| (Intercept) | 2.32E-03 | 0.0000 | 2.32E-03 | 0.0000 | 2.22E-03 | 0.0000 |
| Average return | -8.60E-05 | 0.0010 | - | - | - | - |
| Return on the last trade | - | - | -9.47E-05 | 0.0005 | -1.09E-05 | 0.6885 |
| Previous variance | - | - | - | - | 4.94E-02 | 0.0000 |
| Adjusted R-squared | 0.0000 | - | 0.0000 | - | 0.0026 | - |

**Panel B**

| | Subsequent $\sigma^2$ (Eq. 4) | | Subsequent $\sigma^2$ (Eq. 5) | | Subsequent σ | |
|---|---|---|---|---|---|---|
| | Coef | p-value | Coef | p-value | Coef | p-value |
| (Intercept) | 2.21E-03 | 0.0000 | 2.17E-03 | 0.0000 | 3.00E-02 | 0.0000 |
| Previous variance | 2.21E-03 | 0.0000 | 4.69E-02 | 0.0000 | - | - |
| Expected return | | | - | - | - | - |
| Difference of last return | -1.63E-03 | 0.0003 | - | - | - | - |
| Positive diff. of last return | - | - | 4.72E-03 | 0.0000 | 6.65E-03 | 0.0071 |
| Negative diff. of last return | - | - | -7.78E-03 | 0.0000 | -1.48E-02 | 0.0000 |
| Previous volatility | - | - | - | - | 2.32E-01 | 0.0000 |
| Adjusted R-squared | 0.0027 | - | 0.0031 | - | 0.0386 | - |

**Panel C**

| | Subsequent σ (Eq. 6) | | Subsequent σ | | Subsequent σ if Equity>=Median | | Subsequent σ if Equity<Median | |
|---|---|---|---|---|---|---|---|---|
| | Coef | p-value | Coef | p-value | Coef | p-value | Coef | p-value |
| (Intercept) | 3.08E-02 | 0 | 3.08E-02 | 0.0000 | 3.09E-02 | 0.0000 | 3.16E-02 | 0.0000 |
| Difference of last return | -4.11E-03 | 0.0135 | - | - | - | - | - | - |
| Positive diff. of last return | - | - | 5.53E-03 | 0.0251 | 7.49E-03 | 0.0429 | 2.43E-03 | 0.4627 |
| Negative diff. of last return | - | - | -1.35E-02 | 0.0000 | -9.93E-03 | 0.0098 | -1.47E-02 | 0.0000 |
| Previous volatility | 2.30E-01 | 0 | 2.28E-01 | 0.0000 | 1.99E-01 | 0.0000 | 2.48E-01 | 0.0000 |
| Equity | -2.06E-09 | 0 | -2.06E-09 | 0.0000 | -1.61E-09 | 0.0000 | -5.31E-08 | 0.0000 |
| Cash dummy | -5.33E-04 | 0.0008 | -5.25E-04 | 0.0010 | -5.60E-04 | 0.0213 | -9.45E-04 | 0.0000 |
| IRA dummy | -1.66E-03 | 0 | -1.67E-03 | 0.0000 | -3.16E-03 | 0.0000 | -1.96E-04 | 0.2380 |
| Margin dummy | 1.50E-03 | 0 | 1.49E-03 | 0.0000 | 2.57E-03 | 0.0000 | 1.37E-04 | 0.4620 |
| Adjusted R-squared | 0.0419 | - | 0.0419 | - | 0.0348 | - | 0.0467 | - |

**Panel D**

| | Subsequent σ for cash account | | Subsequent σ for IRA account | | Subsequent σ for margin account | |
|---|---|---|---|---|---|---|
| | Coef | p-value | Coef | p-value | Coef | p-value |
| (Intercept) | 3.00E-02 | 0.0000 | 2.84E-02 | 0.0000 | 3.06E-02 | 0.0000 |
| Positive diff. of last return | 5.11E-02 | 0.0000 | 7.26E-03 | 0.1573 | -1.28E-02 | 0.0388 |
| Negative diff. of last return | -9.60E-04 | 0.9195 | -3.50E-03 | 0.4974 | -1.77E-02 | 0.0009 |
| Previous volatility | 2.44E-01 | 0.0000 | 2.60E-01 | 0.0000 | 2.66E-01 | 0.0000 |
| Equity | -6.65E-09 | 0.0000 | -4.80E-09 | 0.0000 | -9.63E-10 | 0.0000 |
| Adjusted R-squared | 0.0531 | - | 0.0565 | - | 0.0479 | - |

Notes: The table represents regression results for equations one to to six and their modified versions in Panels A, B, C, D. The dependent variables are listed in the columns. The Coef columns represent the estimated coefficients for the parameters listed in the rows, whereas the p-value columns stand for the probability of an incorrect rejection of the zero null hypothesis.

In Table 2 we provide the empirical results of the estimations: results for groups of regressions one to to six and their modified versions in Panel A, B, C and D. Results of the first four regressions indicate that regardless of the type of return, the aggregate effect of previous outcomes on risk attitude is significantly negative even if the previous variance is included, which supports the theory of dynamic loss-aversion. Even though, we find a minor increase in the significance by changing the reference point from the average return to the return relative to the price of the last buy transaction first, then to the return relative to the historical expected return second, the extremely low adjusted R-squared values indicate non-linear dynamics or missing variables. Regression five yields a possible

reason for this latter finding: gains and losses have a distinct effect on risk attitude, although, separating the previous outcomes by their sign does add a lot to the goodness-of-fit of the latter models.

This problem is well handled by changing the risk measure to volatility: the sixth regression shows that the adjusted R-squared value jumps.

Results of the volatility estimation of seventh regression indicate four main findings: first, the aggregate effect of previous outcomes is significantly negative again; second, equity has negative effect on risk-appetite indicating that investors holding larger amounts in capital assets invest into less risky portfolios; third, market participants with cash and retirement (IRA) accounts also avoid risk shown by their negative coefficient; fourth, margin account holders have higher appetite for risk as shown by the positive relationship between subsequent volatility and the margin dummy.

Altogether, regressions in Panel C all indicate a similar pattern as before: negative differences relative to the expected return have a significant and negative effect on the subsequent risk-appetite, whereas positive differences are either much less significant or not significant at all. In particular, regressions nine and ten show that choices of high-income investors are just as sensitive to previous outcomes as low-income investors.

In Panel D regression results show a somewhat mixed picture: although coefficients are not significant everywhere, the previous patterns apply to every subgroup except for the coefficient of the positive previous return of margin account holders. In this latter group, both previous gains and losses are significantly negative leading to lower and higher subsequent volatility respectively.

Altogether, we find similar results to the aggregated regression of Eq. (6) and its adjustment for separated gains and losses. Although, for positive deviations from the expected return we find a statistically significant positive effect on subsequent volatility, we argue that the low p-values are due to the extremely high number of observations. According to OT, positive deviations from the expected return are also negatively correlated with subsequent volatility; nevertheless, since volatility is non-negative, huge realized gains lead to exactly the same portfolio choice (i.e. the risk-free asset) as a gain that is just high enough to cover two subsequent periods of the required return. Therefore, positive returns higher than a relatively small level (at least twice of the expected return) cannot be described by a linear relationship with volatility but are driven by a random process. This leads to the fact that for a reasonable number of observations, where the case of "too big to fail" does not apply, p-values of the positive coefficient should not indicate a significant effect. The last three regressions in Panel C (eighth to tenth regressions), in which the p-value of the coefficient of previous gains is much higher than that of losses, suggest such relationship; however, for such high number of observations a tiny effect may prove to be significant. We argue that this effect may be due to a non linear relationship between previous gains and volatility.

A methodologically solid way to handle this non-linearity would be to use a simple dummy variable for positive shocks. The intuition behind this idea is that if the expected return is relatively very small compared to the positive shocks, then, shocks exceeding this expected return have a constant effect on volatility, since investors would not and cannot reduce their required return and portfolio volatility to values below zero: they hold assets providing at least the risk-free return with zero volatility. Therefore, there is a discontinuity in the model for gains, which can be handled with the use of a dummy variable.

In the followings, we compare the results of the aforementioned model applying a dummy variable for gains and the model assuming a linear relationship between previous gains and subsequent volatility. Table 3 represents our findings.

Table 3: Regression results of volatility dynamics

| | **Subsequent σ** | | | |
|---|---|---|---|---|
| | **Coef** | **p-value** | **Coef** | **p-value** |
| **(Intercept)** | 3.08E-02 | 0.0000 | 3.11E-02 | 0.0000 |
| **Positive diff. dummy** | - | - | -6.12E-04 | 0.0000 |
| **Positive diff. of last return** | 5.53E-03 | 0.0251 | - | - |
| **Negative diff. of last return** | -1.35E-02 | 0.0000 | -9.73E-03 | 0.0001 |
| **Previous volatility** | 2.28E-01 | 0.0000 | 2.29E-01 | 0.0000 |
| **Equity** | -2.06E-09 | 0.0000 | -2.07E-09 | 0.0000 |
| **Cash dummy** | -5.25E-04 | 0.0010 | -5.49E-04 | 0.0006 |
| **IRA dummy** | -1.67E-03 | 0.0000 | -1.67E-03 | 0.0000 |
| **Margin dummy** | 1.49E-03 | 0.0000 | 1.48E-03 | 0.0000 |
| **Adjusted R-squared** | 0.0419 | - | 0.0420 | - |

Notes: The table represents regression results for two regressions between previous outcomes and subsequent volatility. The dependent variable is listed in the columns, the Coef columns represent the estimated coefficients for the independent variables listed in the rows, whereas the p-value columns stand for the probability of an incorrect rejection of the zero null hypothesis.

The results indicate three important findings: first, by avoiding the discontinuity problem the regression model support our idea of a positive relationship between previous gains and volatility instead of linearity; second, this relationship becomes much more significant than in the linear model and therefore, all the variables have extremely low p-values; third, the adjusted R-squared also increases in the new model suggesting a better fit with the dummy variable. Hence, altogether the findings support the negative relationship proposed in the theoretical model.

In conclusion, we argue that the results presented in this subsection confirm the empirical validity of the behavioral side of our explanation. The aggregate coefficient of previous outcomes is negative and significant everywhere, even in regressions where other control variables are included. In particular, it seems irrelevant whether we test the effect on low- or high-income investors; the pattern emerges for all of them. Therefore, as a confirmation of the theoretical model, we find that previous outcomes indeed affect asset allocation and, subsequent to losses and gains, yield a money inflow into assets with higher and lower risk respectively. This finding is confirmed in existing literature on mutual fund activity as well, in which a negative relationship was found between returns and subsequent money inflows (Warther, 1995; Goetzman and Massa, 1999; Edelen and Warner, 1999) and between contemporaneous inflow of equity and bond funds (Goetzmann et al., 2000). Therefore, we argue that the model can capture and explain the unexpected changes in the demand for capital assets.

**Estimating a volatility model**

Based on the findings presented above, the empirical estimation of the theoretical model is presented in the followings. In this section the unit-root volatility model of OT is analysed. The α and β parameters are estimated for the return and volatility time series of the daily values of the CRSP value-weighted equity index using both weekly and monthly periods. The return is defined as the sum of the logarithmic daily returns. The volatility is calculated as the standard deviation of the returns during the given period; however, since this would show the daily volatility, it is multiplied by the ratio of the standard deviation of weekly returns divided by the standard deviation of daily returns (the adjustment to weekly from daily sampling). The estimation is based on simulating an error term of

$$e_t = r_t - \left(r_{f,t} + \beta\sigma_{t-1} + \alpha\left(\mathrm{r}_{t-1} - r_{f,t-1} - \beta\sigma_{t-1}\right)\right). \quad (7)$$

where α∈[-1,0] and β∈[0,1]. Here, the error term is not homoscedastic, therefore, we define the standardized error ut as

$$u_t = \frac{e_t}{\sigma_t}. \quad (8)$$

Since these parameters are particularly sensitive to the underlying assumptions, first the distribution of the error is fitted based on maximum likelihood, where $u_t$ is assumed to follow a scaled Student's-t distribution with $E(u_t) = 0$. Then, we apply a Kolmogorov-Smirnoff test to measure the significance of the difference between the empirical and estimated distribution functions. The higher the significance, the better the fit, therefore, the (α,β) pair yielding the highest p-value indicates the best fit of a distribution conditional to $E(u_t) = 0$; in other words, this pair is considered to provide the least significant error terms.

The numerical simulation results yield $\begin{bmatrix}\alpha\\ \beta\end{bmatrix} = \begin{bmatrix}-0.03\\ 0.21\end{bmatrix}$ with a p-value of 0.85 and $\begin{bmatrix}\alpha\\ \beta\end{bmatrix} = \begin{bmatrix}-0.07\\ 0.32\end{bmatrix}$ with a p-value of 0.93 using weekly and monthly periods respectively. Both results confirm that investors include previous outcomes as a negative proxy for their required return while the positive relationship between risk and required return stays intact. The particularly high p-values indicate that the error terms are fitted well using scaled Student's-t distributions; thus, the test results are robust.

It is worth mentioning that the model presented above describes the dynamics of the volatility of the whole market. However, as presented above, asymmetric volatility affects individual assets as well. We argue that this phenomenon stands on the fact that market and asset returns are highly correlated, especially in periods of greater continuous shocks (e.g. the financial crisis) that affect volatility significantly. So, we present a correlation test between the volatilities of the index and individual assets. The findings presented in Table 4 are consistent with the proposed reasoning for individual asymmetry.

Table 4: Correlation between market and asset volatilities

| | Weekly analysis | Monthly analysis |
|---|---|---|
| **Positive correlations** | 500 | 499 |
| **significant at 5%** | 497 | 492 |
| **Negative correlations** | 0 | 1 |
| **significant at 5%** | 0 | 0 |

According to weekly analysis, volatility correlation with the index is positive for all the 500 individual assets, although in three cases it is not significant. Nonetheless, these three latter assets (in particular, the equities with tickers "MNST", "NAVI" and "NWSA") have only become recently listed in the stock exchange, and therefore, correlation is tested on a much shorter interval than in the other cases. Hence, in these three cases the significance test yields low p-values due to the insufficient number of observations.

Applying monthly periods a similar pattern arises. Out of the 8 insignificant correlation coefficients 6 can be attributed to short available time series here as well. Altogether the positive correlation between individual assets is a robust pattern both in our weekly and monthly analysis, and hence, it is indeed a reasonable cause for the asymmetric volatility of individual assets.

## CONCLUDING REMARKS

We find that the derivations of the theoretical model of Ormos and Timotity (2015) are empirically sound. Therefore, their recent theoretical explanation for asymmetric volatility is supported from both theoretical and empirical sides as follows.

First, we show that, in line with their findings, individuals tend to become less risk-averse (or risk-seeking until a given point) and more risk-averse subsequent to losses and gains respectively. This pattern confirms the existence of intertemporal mental framing, that is, investors tend to aggregate in time and adjust their portfolio accordingly.

Second, our empirical parameter estimation in discrete time indicates that the proposed model of OT indeed outperforms the simple random walk model: we confirm the significance of the predicted negative effect of previous outcomes on subsequent volatility, whereas, the positive relationship between simultaneous volatility and expected return remains significantly positive.

## ACKNOWLEDGEMENTS

We gratefully acknowledge the help of Terry Odean, who provided us with the individual trading dataset. We also would like to express our gratitude for the thoughtful remarks of Adam Zawadowski, which have significantly contributed to our paper. We thank Zsolt Bihary and Niklas Wagner for their comments and suggestions of at the 6th Annual Financial Market Liquidity Conference 2015 at Corvinus University of Budapest. Mihály Ormos acknowledges the support by the János Bolyai Research Scholarship of the Hungarian Academy of Sciences. Dusán Timotity acknowledges the support by the Pallas Athéné Domus Scientiae Foundation. This research was partially supported by Pallas Athene Domus Scientiae Foundation.

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