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## Time-Induced Stress Effect on Financial Decision Making in Real Markets: The Case of Traffic Congestion

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# Time-Induced Stress Effect on Financial Decision Making in Real Markets: The Case of Traffic Congestion<sup>1</sup>

## Abstract

We study the role of stress induced by time constraints on investors' decision making. The need to perform contemporaneous tasks and external interference such as arriving unexpectedly late to work, might exacerbate acute stress and its impact on decision making. Accumulated laboratory research suggests that time stress may impact financial decisions, mainly in the loss domain. We contribute to the literature studying this issue in real financial markets, as the real markets distinguish themselves from laboratory experiments through repeated situations, aggregation of outcomes and extremely high monetary stakes. We use data on traffic congestion, weather conditions and derivative prices. Our main dependent variable is the slope of the implied volatility function (IVF) of options on RTS futures (cf. Bollen and Whaley, 2004) at the left-hand side of the volatility smile. We find that, controlling for relevant factors, this slope at open of the main trading session is higher subsequent to morning traffic jams, suggesting that investors under stress assign higher weights to extreme loss scenarios.

*Keywords: behavioral finance, implied volatility function, weighting of extreme scenarios*

*JEL codes: G13, G02*

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<sup>1</sup> We thank Yandex for providing us with traffic congestion data for Moscow for September 2011 – September 2013.

## I. Introduction

### *Affective states and Decision making*

Accumulated research on human behavior has documented the role of affective states in forming individuals' judgments and decision making (cf. Schwarz and Clore, 1983). Of specific interest to our research, the effect of mood on decisions and outcomes in financial markets has been investigated, and given rise to evidence that financial decision making might deviate from rationality, and be subject to factors, such as weather-induced affective states (Saunders, 1993; Hirshleifer and Shumway, 2003; Chang et al., 2008); international soccer game results (Edmans et al. (2007); and even air pollution levels (Levy and Yagil, 2011). Moreover, as documented by Siganos et al. (2014), daily sentiment captured by Facebook's Happiness Index has been found to be correlated to trading volume and return volatility. Lastly, Kamstra et al. (2000, 2010) show the impact of interruptions to investors' sleep patterns, due to daylight saving time changes.

Hirshleifer (2001) sketches a framework for understanding the psychology of investors and their financial decisions, influencing security prices. According to such framework, there is interplay between investors' mood and feelings and their decisions. For instance, economic risk aversion, as well as its psychological counterparts, loss aversion and regret aversion, may reflect calculated avoidance of unpleasant future outcomes, while, at the same time, contemporaneous mood and emotions may affect the investors' perceptions and choices with respect to risk (see also Mann, 1992). Further, Loewenstein et al. (2001) postulate their 'risk-as-feelings' hypothesis, asserting that emotional states navigate decision making under risk, deviating thereby from the asserted behavior presumed in normative models, and Kuhnen and Knutson (2011) analyze the influence of affect on beliefs, preferences, and the formation of financial decisions.

Importantly, simultaneous fluctuations in investors' affective states due to common factors (e.g., weather and seasons), might not average out, thus leave traces in aggregate market outcomes. One such factor is Seasonal Affective Disorder (SAD), a type of circannual depression affecting a vast majority of the population, especially in northern regions. The biological mechanism underlying SAD involves biochemical imbalances in the hypothalamus resulting from seasonal shortening of photoperiod (Rosenthal et al., 1984). Kamstra et al. (2003, 2012) show the effect of SAD-induced mood on stock returns. Kliger and Levy (2003a, 2003b) show the effect of weather-induced mood on

investors' probability judgments and risk tolerance; Kliger and Levy (2008) employ SAD and cloudiness to explain variations in investors' subjective probability perceptions (manifested in their probability weighting functions); Kliger et al. (2012) document SAD effects on the demand for initial public offerings; Kramer and Weber (2012) relate SAD to seasonally-varying risk aversion; Kliger and Kudryavtsev (2013) show seasonal effects on investors' reactions to news; and Kliger et al. (2015) document SAD effects on seasoned art auction prices.<sup>2</sup>

Two directions linking individuals' mood and their attitude toward risk have been proposed in the psychological research. The first direction asserts that positive mood increases risk aversion (c.f. mood maintenance theory, MMH, Isen, 1984 and 2000)<sup>3</sup>, while the second direction that positive mood decreases risk aversion (see Molin et al., 1996; Young et al., 1997). Two behavioral explanations corroborate the first direction: (i) good mood elevates people's reference point (while bad mood lowers it), and their preferences possess the property of loss aversion, and (ii) good mood makes people behave cautiously, such as to avoid actions which might "spoil" their mood and, consequently, make them regret their decision.

### *Stress effects on financial decisions*

In the current research, we study the effect of stress on financial decision making. Stress, as a biological concept, is an emotional factor that causes mental, as well as bodily, tension. It may be either external, i.e., arrive from the surrounding environment, or internal, such as from a medical condition. Financial decision making, especially at the trading floor, is often made under stress caused by the considerable economic consequences of the decisions and the need to make them within time constraints.

Starcke and Brand (2012) review studies that investigated acutely induced laboratory stress effects on decision making. The picture emerging from the reviewed studies is that stress may cause shifts in the performance of the decision makers. Likely, it triggers cardio-vascular, hormonal, and neural reactions that may affect fine-tuned decision making. While the effects may be detrimental in some

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<sup>2</sup> Mood effects on risk attitudes have been also documented experimentally. See, e.g., Isen and Patrick, 1983; Arkes, Herren, and Isen, 1988; Isen, Nygren, and Ashby, 1988; Nygren, Isen, Taylor, and Dulin, 1996; Nygren, 1998; and Bassi et al., 2013.

<sup>3</sup> MMH postulates that people strive to maintain positive mood states. Additionally, it links positive mood and 'shallow thinking', as detailed information processing is presumed to undermine pleasant mood states (e.g., Mackie and Worth (1989), Schwarz (2001)).

situations (e.g., when the use of higher level systems is called for), there are also situations in which they may be beneficial. As the authors conclude, this corroborates the proposed evolutionary value of “fight or flight” stress responses. Moreover, if stress is perceived as a challenge, rather than as a threat, cardiovascular reactions may prove to provide additional cognitive resources and allow, thus, more fine-tuned decision making.

Porcelli and Delgado (2009) conducted experiments containing recognition memory and financial decision making tasks. During the recognition memory tasks, the subjects (university students) were exposed to either extrinsic acute stress, or no-stress control procedure. Results indicate that under stress, subjects’ financial choices exhibited a stronger reflection effect, suggesting thereby that stress modulates risk taking, presumably exacerbating behavioral biases in decision making. In the context of dual-process mechanisms, the authors interpreted the results as suggesting that under stress, decision makers fall back to automatized (system 1) reactions.

Buckert et al. (2014) examined acute stress influences on economic decision making under risk and ambiguity of healthy young participants, using financially incentivized lotteries and varying the domain of decision making, as well as the expected value of the risky prospect. In order to eliminate possible effects of independent learning processes, no feedback was provided to the participants. For gambling under risk, a subgroup of participants that showed a robust cortisol response to acute stress, manifested more risk seeking for gains. However, acute stress did not affect gambling under ambiguity. They concluded that stress as indicated by a reliable cortisol response may affect risk taking, independent of feedback-based learning processes. Yet, the effect seems to be highly dependent on task characteristics.

Coates and Herbert (2008) found that as market uncertainty, measured by market volatility, increased, traders in the City of London experienced a sustained increase in their mean daily stress hormone cortisol levels. Following this study, Kandasamy et al. (2014), questioned whether such elevated cortisol levels shift risk preferences. To that end, they employed a double-blind, placebo-controlled, experiment, in which they have raised volunteers’ cortisol levels to the same extent and duration observed by Coates and Herbert in the traders. They then tested the utility and probability weighting functions (PWFs) underlying the traders’ risk taking, and found that participants became more risk averse and their PWFs became more distorted among men relative to women.

### *Time pressure as stress factor*

Our study of the role of stress in investors' decision making focuses on stress induced by time constraints. Evidently, this source of stress plays key role in financial decision making, and especially so at the trading floor. Arguably, the immediacy of trading decisions thrusts floor traders to integrate system-1 and system-2 processes into their decision making tasks. Moreover, the need to perform contemporaneous tasks, as well as external interference, such as arriving unexpectedly late to work, might exacerbate acute stress and its impact on decision making.

Ben Zur and Breznitz (1981) let subjects chose between gamble pairs under varying time pressure conditions. The gambles pairs were equated for expected value but differed in variance, amounts to win and lose and their respective probabilities. The subjects have chosen less risky gambles under high (8 seconds), as compared to medium (16 sec.) and low (32 sec.) time pressure. In addition, subjects tended to spend more time observing the gambles' negative dimensions (amount to lose and probability of losing), while under low time pressure they preferred observing their positive dimensions. Indeed, in the context of decision making under certainty, time pressure caused attribution of more weight to negative information in purchase options (Wright 1974), as well as enhanced avoidance of expected pain (Breznitz 1974). Accordingly, Ben Zur and Breznitz suggested that time pressure tends to emphasize the negative aspects of the decision problem at stake.

Two experiments conducted by Kocher et al. (2013) on university undergraduates studies the effects of time pressure on various prospects. While time pressure had no effect on risk attitudes for gains, it increased risk aversion for losses. Moreover, in the case of mixed prospects, time-constrained participants manifested more loss aversion and gain seeking, depending on the prospects' framing.

Wegier and Spaniol (2015) conducted two experiments on student subjects to compare the effects of time pressure on risky financial decisions between description- and experience-based decisions, across both gain and loss domains. In description-based choices, they found that time pressure decreased risk seeking for losses, whereas for gains there was a trend in the opposite direction. In experience-based choice, no impact of time pressure was observed on risk-taking.

The abovementioned findings suggest that stress induced by time pressure may exert impact on financial decision making. In particular, the impact is expected to be found in the loss domain. One should note, however, that while this conjecture is based on a vast research body, virtually all of the research thus far has been based on laboratory experiments, most of them conducted on students. The

goal of our study is to shed light on the effect of stress on the decisions of professional investors, in their real-life financial arena. To the best of our knowledge, no such research has been conducted to date.

The exploration of time-induced stress in real financial markets, rather than in the lab, has quadruple-fold merits. First, in markets, unlike in most laboratory experiments, people are confronted with repeated situations and have the opportunity to learn from their own and others' experience. Second, laboratory results might not carry over to the market because market prices are aggregate outcomes in which individual violations of rationality may be washed out. Third, individuals may apply different decision rules when they are confronted with real-life situations, than the rules they apply in laboratory setups. Last, but not least, decisions in real-life financial markets involve extremely high monetary stakes, incomparable to typical laboratory payments.

The rest of the paper is structured as follows: Section II describes the data and introduces our methodology, Section III discusses our main results, robustness checks are presented in Section IV, Section V concludes.

## **II. Data and Methodology**

In our study we use data on traffic congestion, weather conditions and stock and derivative market data. Whereas most of the data are quite standard, construction of our main explanatory variable, traffic congestion, as well as of the main dependent variable, slope of the implied volatility function, is somewhat more sophisticated, and deserves somewhat more comprehensive treatment, which we detail in separate subsections below.

### **II.1 Description of the traffic congestion variable**

We obtain traffic congestion values from Yandex for Moscow city for the period from September 1, 2011 to September 27, 2013. The measure provided to us by Yandex is the so-called “deceleration coefficient”, DC, which is the time needed to cover some reference distance related to a free traffic situation. DC for Moscow city is an average of the DCs for all streets covered by Yandex in Moscow (which are virtually all non-pedestrian streets). We are provided with values at half-hour frequency, which are averages of all recorded values across half-hour window centered at reporting time. E.g. DC for 8:30 am is the average deceleration on all streets of Moscow from 8:15 am to 8:45 am. Our

primary focus is the period prior to the opening of the Moscow Exchange at 10 am, as traders supposedly drive during that time to their working places, at the center of town. Thus, we average the values for 8:30, 9:00 and 9:30 to obtain the morning average deceleration coefficient (effectively capturing the state of Moscow traffic from 8:15 to 9:45). Table 1 (left column) gives an overview of the statistical properties of this measure. By design, the range of admissible values is bounded by one from below.

Table 1. Descriptive statistics for traffic congestion

|              | Traffic congestion,<br>DC | Unexpected traffic<br>congestion, UDC |
|--------------|---------------------------|---------------------------------------|
| Mean         | 1.6131                    | 0.0000                                |
| Median       | 1.6040                    | -0.0063                               |
| Maximum      | 2.5261                    | 0.5830                                |
| Minimum      | 1.0015                    | -0.7425                               |
| Std. Dev.    | 0.2079                    | 0.1361                                |
| $\rho_1$     | 0.708                     | -0.127                                |
| Observations | 526                       | 525                                   |

The Mean traffic congestion, of 1.6, informs that, on average, drivers need 60% more time to get to their working place in the morning compared to doing the same travel when streets are uncongested. In the worst case in our data sample, they needed 2.5 as much time; at best, the traffic situation hardly causes any deceleration in the morning. Note that traffic congestion in the morning is strongly autocorrelated ( $\rho_1$ , the serial correlation coefficient, is 0.7) – indeed, jams are frequently caused by slow changing factors: weather conditions, construction works, seasonality of employment, etc. As our focus is on the effect of stress caused by traffic conditions, we single out traffic congestion shocks, i.e. unexpected degree of traffic jams (as we believe that the expect traffic condition does not raise drivers' stress levels substantially). To obtain the unexpected part we regress the traffic congestion variable, DC, upon its lag, monthly dummies and day-of-the-week dummies, in order to capture seasonality and latent slow changing factors:

$$DC_t = \alpha_1 DC_{t-1} + \delta_1 D_{Monday} + \delta_2 D_{Tuesday} + \delta_3 D_{Wednesday} + \delta_4 D_{Thursday} + \delta_5 D_{Friday} + \delta_6 D_{Saturday} + \delta_7 D_{Sunday} + \sum_{m=1}^{12} \gamma_m D_m + \varepsilon_t \quad (1)$$



We use the residuals from Equation (1) as the unexpected traffic congestion variable. The rightmost column of Table 1 shows that the magnitude of the unexpected congestion is about one half of the raw ‘deceleration coefficient’, and the autocorrelation is substantially smaller (and of a different sign).

## II.2 Description of other variables

Table 2: Variable definition

| Variable                        | Definition   | Source   |
|---------------------------------|--|--|
| Unex. Traffic congestion        | Residuals of the regression of the DC measure upon day of the week dummies with an autoregressive term (see eq. 1)   | Yandex, Own calculations   |
| Precipitation 6 am              | precipitation at 6 am in mm  | VDNKh weather station<br><a href="http://www.pogodaiklimat.ru/weather.php?id=27612">http://www.pogodaiklimat.ru/weather.php?id=27612</a> |
| Visibility 9 am                 | visibility at 9 am in km   | VDNKh weather station<br><a href="http://www.pogodaiklimat.ru/weather.php?id=27612">http://www.pogodaiklimat.ru/weather.php?id=27612</a> |
| Cloudiness 9am                  | The average cloudiness, measured on the scale from 1 to 10 points at 9 am  | VDNKh weather station<br><a href="http://www.pogodaiklimat.ru/weather.php?id=27612">http://www.pogodaiklimat.ru/weather.php?id=27612</a> |
| Temperature 9 am                | Temperature, measured 2 m. above the ground, at 9 am (C)   | VDNKh weather station<br><a href="http://www.pogodaiklimat.ru/weather.php?id=27612">http://www.pogodaiklimat.ru/weather.php?id=27612</a> |
| US slope                        | The difference between the (interpolated) implied volatility of options on Standard and Poor’s 500 Index with 90% moneyness and the implied volatility of options with 100% moneyness on the same underlying, normalized by the latter <sup>4</sup> Continuous one-month volatility series for Moneyness 90 and 100 are obtained directly from Datastream (Datastream series SPXMONEY90, SPXMONEY100; datatype O1) | Thomson Reuters<br>Datastream, own calculations  |
| Log RTSI futures trading volume | Natural logarithm of the daily trading volume (# of contracts)   | Thomson Reuters<br>Datastream, own calculations  |

<sup>4</sup> Moneyness is measured here as the strike to spot ratio

|                            |   |   |
|----------------------------|---|---|
|                            | of the continuous futures (de-facto sum of volumes of all traded futures) on the RTS index. (Datastream series RTSCS00, datatype VO; <sup>5</sup> ) |   |
| RTSVX                      | RTSVX, Moscow exchange volatility index (closing value, if not stated differently) <sup>6</sup>   | Thomson Reuters Datastream  |
| VIX                        | VIX, US volatility index (closing value, if not stated differently)   | Thomson Reuters Datastream  |
| RTSI futures return        | net simple return (close-to-close) to the continuous futures on the RTS index (Datastream series RTSCS00) <sup>7</sup>                              | Thomson Reuters Datastream  |
| S&P 500 return             | net simple return of the S&P 500 index (close-to-close); we impute zeroes for trading days in Moscow which are not trading days in US               | Thomson Reuters Datastream  |
| Time to expiration         | Time to option expiration, in calendar days   | Moscow Exchange   |
| Time to expiration squared | Time to option expiration squared, in calendar days squared   | Moscow Exchange, own calculations   |
| Trade- but not working day | A dummy for trading days of the Moscow Stock Exchange, which were state holidays (e.g. January 3-6, 2012)   | Russian official holidays calendar; Moscow Exchange working time calendar |
| Before holiday             | A dummy variable which is 1 on a day immediately prior to official holiday and zero otherwise   | Russian official holidays calendar  |
| After holiday              | A dummy variable which is 1 on a day immediately after an official holiday and zero otherwise   | Russian official holidays calendar  |

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<sup>5</sup> Values for trading days on Saturdays and Sundays were calculated by hand using Moscow Exchange data and the Datastream approach

<sup>6</sup> Values for trading days on Saturdays and Sundays are hand-collected from Moscow Exchange

<sup>7</sup> Values for trading days on Saturdays and Sundays were calculated by hand using Moscow Exchange data and the Datastream approach

### II.3 Description of dependent variables

We obtain our data on RTSI continuous futures prices and volumes as well as RTSVX index values from Datastream,<sup>8</sup> and option prices on RTSI futures and corresponding RTSI futures values directly from the Moscow Exchange. Moscow Exchange resulted from the merger of the two major Russian exchanges Russian Trading System (RTS) and Moscow Interbank Currency Exchange (MICEX) in December 2011. Prior to the merger RTS was the major exchange for trading derivatives, which ran on its FORTS section. Whereas RTS had also a stock trading section, it was way inferior in 2011 to MICEX in terms of volume. Futures and option trading during the period of our study was organized as continuous trading, main trading session opening at 10 a.m. and closing at 18:45. There were no opening or closing auctions for derivatives. Clearing takes place from 14:00 to 14:03 and from 18:45 to 19:00. Moreover, there was also an additional evening session from 19:00 to 23:50. The data we have obtained from Moscow Exchange and Datastream are on the main trading session.<sup>9</sup> The volume of trading in the evening session is substantially lower than during the main session, so that we believe it is negligible. Hence, our open price for a derivative contract is a price of the first transactions performed in course of continuous trading, after 10 am. Correspondingly, closing prices for a futures contract or an option is a price of the last transaction in the main session, before 6.45 pm.

An important feature of options on RTS Futures is that they are so called ‘margining options’ or futures-like options. That means that the buyer does not pay the option premium at the time of purchasing the contract. Instead, the premium is subtracted from her payoff at execution; if she decides not to execute, the premium is paid on option expiration; if the payoff is positive but lower than the premium, the buyer pays the difference to the seller.

In the study we use a set of dependent variables: RTS Futures returns, trading volume of RTS futures, RTS Volatility Index (RTSVX) and the slope of the implied volatility function (IVF) of options on RTS futures. Whereby the first three measures are quite standard and are sufficiently explained in Table 2, construction of the IVF slope is somewhat more specific. As we mainly focus on the risk aversion and perceived probability of extreme events, the slope of the implied

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<sup>8</sup> Values of RTSI continuous futures prices and volumes for trading days on Saturdays and Sundays were calculated by hand using Moscow Exchange data and the Datastream approach; RTSVX values for trading days on Saturdays and Sundays are hand-collected from Moscow Exchange

<sup>9</sup> Whereas it is possible to obtain data on the evening session from Moscow Exchange, Datastream reports only the data for the main session.

volatility curve is our main dependent variable, and its construction deserves thorough explanation.

We calculate the slope of the implied volatility curve following Bollen and Whaley (2004), in five steps. First, we calculate implied volatilities for each option's daily open and close prices (two implied volatilities for each strike per day). We extract implied volatilities from option prices by inverting the modified Black Scholes (1973) formula for futures-like options on futures as underlying (see Black (1976) for options on futures and Moscow Exchange (2011) for the modification for the futures-like options):

$$C = F\Phi\left[\frac{\ln\left(\frac{F}{K}\right) + 0.5\sigma^2T}{\sigma\sqrt{T}}\right] - K\Phi\left[\frac{\ln\left(\frac{F}{K}\right) - 0.5\sigma^2T}{\sigma\sqrt{T}}\right] \quad (2)$$

for call options and

$$P = K\Phi\left[-\frac{\ln\left(\frac{F}{K}\right) - 0.5\sigma^2T}{\sigma\sqrt{T}}\right] - F\Phi\left[-\frac{\ln\left(\frac{F}{K}\right) + 0.5\sigma^2T}{\sigma\sqrt{T}}\right] \quad (3)$$

for put options, where  $F$  denotes the current price of the underlying (RTS futures),  $K$  denotes the strike,  $\sigma$  - the implied volatility,  $T$  - time to expiration, and  $\Phi$  denotes the cdf of the standard normal distribution.<sup>10</sup>

Second, we obtain deltas following the logic of Black and Scholes (1973):<sup>11</sup>

$$\Delta_c = \Phi\left[\frac{\ln\left(\frac{F}{K}\right) + 0.5\sigma^2T}{\sigma\sqrt{T}}\right], \quad \Delta_p = -\Phi\left[-\frac{\ln\left(\frac{F}{K}\right) + 0.5\sigma^2T}{\sigma\sqrt{T}}\right]. \quad (4)$$

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<sup>10</sup> Since the options are written on the futures contract, there is no need to account for dividends. Since the underlying is a futures contract, and the options are futures-like there is no discounting. See also Moscow Exchange (2011) and Black (1976).

<sup>11</sup> We use the fact that formulas for option prices for futures-like options on futures are equivalent to the standard Black-Scholes (1973) definitions with dividend yield and risk-free rate set to zero.

For the purpose of delta estimation we use realized return volatility of the preceding 60 days as the volatility rate  $\sigma$  in Eq. (4), following the approach in Bollen and Whaley (2004).

We estimate both the implied volatilities and corresponding deltas using the RQuantLib library in R.

Third, we divide the options into moneyness categories, according to their moneyness, measured by the deltas of options. We follow the literature (Bollen and Whaley 2004) and use delta rather than the ratio of the underlying price over the strike, and interpret moneyness as the risk-neutral probability of an option to be “in the money” at expiration. A main advantage of this approach is that it takes into account the effect of the volatility of underlying on the likelihood of the option to end up “in the money” at expiration. Thus, it allows intertemporal comparison of slopes, even between periods of different volatility. The categories are summarized in Table 3:

Table 3. Moneyness category definitions

| Category | Labels                            | Range                         |
|----------|-----------------------------------|-------------------------------|
| 1        | Deep in-the-money (DITM) call     | $0.875 < \Delta \leq 0.98$    |
|          | Deep out-of-the-money (DOTM) put  | $-0.125 < \Delta \leq -0.02$  |
| 2        | In-the-money (ITM) call           | $0.625 < \Delta \leq 0.875$   |
|          | Out-of-the-money (OTM) put        | $-0.375 < \Delta \leq -0.125$ |
| 3        | At-the-money (ATM) call           | $0.375 < \Delta \leq 0.625$   |
|          | At-the-money (ATM) put            | $-0.625 < \Delta \leq -0.375$ |
| 4        | Out-of-the-money (OTM) call       | $0.125 < \Delta \leq 0.375$   |
|          | In-the-money (ITM) put            | $-0.875 < \Delta \leq -0.625$ |
| 5        | Deep out-of-the-money (DOTM) call | $0.02 < \Delta \leq 0.125$    |
|          | Deep in-the-money (DITM) put      | $-0.98 < \Delta \leq -0.875$  |

Fourth, we average the implied volatility of all options of each type, which delta fall within the range of the category, to obtain category-type average IV (category-types being DITM call, DOTM put and

so on). Then we average implied volatilities of puts and calls falling into each category. If there are no options in the range, missing observations are generated.<sup>12</sup>

Fifth, we calculate the implied volatility slope by subtracting implied volatility of Category 2 from the implied volatility of Category 3 and normalize the difference by the implied volatility of Category 3:

$$Slope_{j,t} = \frac{\sigma_{j,t,CAT2} - \sigma_{j,t,CAT3}}{\sigma_{j,t,CAT3}} \quad (5)$$

$j = open, close$

Furthermore we calculate also the slopes from call options and put options separately, as  $(\sigma_{ITM call} - \sigma_{ATM call}) / \sigma_{ATM call}$  and  $(\sigma_{OTM put} - \sigma_{ATM put}) / \sigma_{ATM put}$  respectively.

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<sup>12</sup> We pursue two approaches of treating these missing observations: (1) in cases where the implied volatility of put (call) is missing, take the implied volatility of call (put) only, instead; (2) declare the implied volatility of such category as missing. The former approach allows preserving more observations, while the latter relies only on existing data. We report result for both approaches.

Table 5a. Descriptive statistics for implied volatilities of options on RTS index futures, call

|                          | DITM   | ITM    | ATM    | OTM    | DOTM   |
|--------------------------|--------|--------|--------|--------|--------|
| <i>Panel A: At open</i>  |        |        |        |        |        |
| Mean                     | 0.3884 | 0.3274 | 0.3079 | 0.2897 | 0.2902 |
| Median                   | 0.3429 | 0.3083 | 0.2968 | 0.2790 | 0.2805 |
| Std. Dev.                | 0.1657 | 0.1082 | 0.0932 | 0.0853 | 0.0824 |
| Observations             | 307    | 489    | 505    | 523    | 523    |
| <i>Panel B: At close</i> |        |        |        |        |        |
| Mean                     | 0.3710 | 0.3192 | 0.3014 | 0.2823 | 0.2832 |
| Median                   | 0.3431 | 0.3075 | 0.2889 | 0.2701 | 0.2715 |
| Std. Dev.                | 0.1444 | 0.1044 | 0.0913 | 0.0839 | 0.0811 |
| Observations             | 308    | 488    | 502    | 524    | 523    |

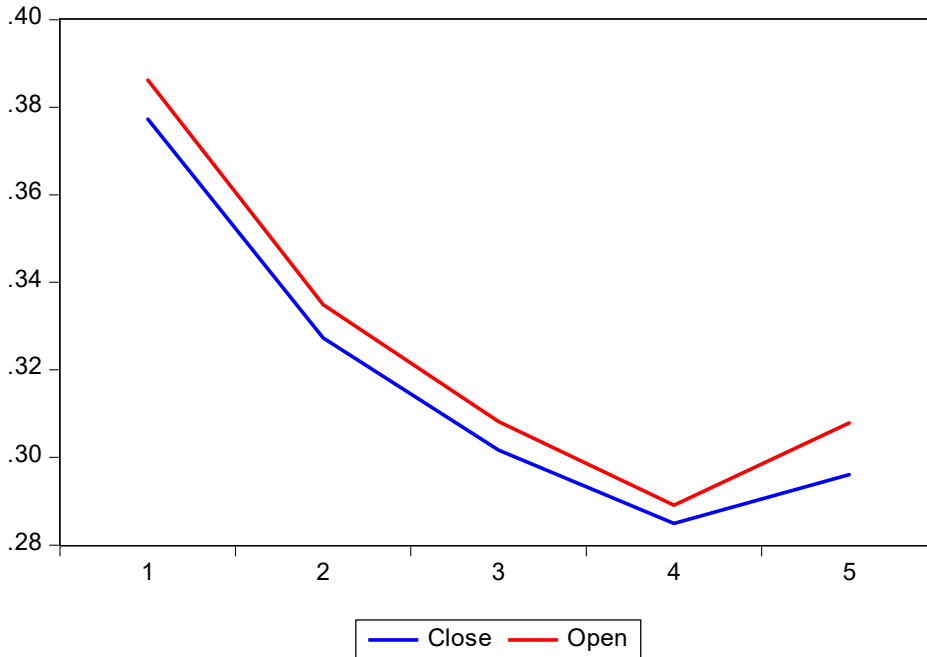
The table presents descriptive statistics of implied volatility (IV) for the call options with different moneyness for the sample 9/2/2011-9/27/2013 (delta calculated using the past 60 days realized volatility as volatility rate)

Table 5b. Descriptive statistics for implied volatilities of options on RTS index futures, put

|                          | DOTM   | OTM    | ATM    | ITM    | DITM   |
|--------------------------|--------|--------|--------|--------|--------|
| <i>Panel A: At open</i>  |        |        |        |        |        |
| Mean                     | 0.3778 | 0.3376 | 0.3080 | 0.2834 | 0.3628 |
| Median                   | 0.3621 | 0.3239 | 0.2958 | 0.2611 | 0.3180 |
| Std. Dev.                | 0.1211 | 0.1077 | 0.0941 | 0.0974 | 0.1709 |
| Observations             | 520    | 521    | 499    | 473    | 239    |
| <i>Panel B: At close</i> |        |        |        |        |        |
| Mean                     | 0.3724 | 0.3294 | 0.3013 | 0.2812 | 0.3203 |
| Median                   | 0.3576 | 0.3168 | 0.2891 | 0.2612 | 0.2917 |
| Std. Dev.                | 0.1218 | 0.1053 | 0.0932 | 0.0962 | 0.1173 |
| Observations             | 521    | 522    | 498    | 477    | 269    |

The table presents descriptive statistics of implied volatility (IV) for the put options with different moneyness for the sample 9/2/2011-9/27/2013 (delta calculated using the past 60 days realized volatility as volatility rate)

**Figure 1** Estimated implied volatility functions of RTS futures options at open and close



The graph visualizes the implied volatility curves, plotted against the moneyness categories 1-5 (described in Table 3), for options at open (red) and close (blue). Average implied volatility (y-axis) for each category (x-axis) is obtained in the first four steps of the procedure, explained in Section II.

**Table 6.** Descriptive statistics for slopes of the implied volatility function, 9/2/2011-9/27/2013

|                          | Slope  | Slope* | Slope: Call | Slope: Put |
|--------------------------|--------|--------|-------------|------------|
| <i>Panel A: At open</i>  |        |        |             |            |
| Mean                     | 0.0906 | 0.0905 | 0.0809      | 0.1015     |
| Median                   | 0.0878 | 0.0879 | 0.0785      | 0.0936     |
| Std. Dev.                | 0.0748 | 0.0760 | 0.1254      | 0.0650     |
| Observations             | 465    | 504    | 473         | 496        |
| <i>Panel B: At close</i> |        |        |             |            |
| Mean                     | 0.0923 | 0.0922 | 0.0843      | 0.0996     |
| Median                   | 0.0912 | 0.0900 | 0.0848      | 0.0965     |
| Std. Dev.                | 0.0667 | 0.0662 | 0.1194      | 0.0398     |
| Observations             | 463    | 503    | 469         | 496        |

The table presents descriptive statistics for the slopes of the implied volatilities curve, obtained in five steps, as explained in Section II, from options on the RTS futures. Thereby ‘Slope’ denotes the normalized difference between categories 2 and 3, as in Eq. 5, whereby the implied volatility for a category is dropped if the implied volatility of either calls or puts in that category is missing; ‘Slope\*’ is calculated analogically (Eq. 5), but uses non-missing implied volatility as the volatility for the category, if one of the two IVs in the category is missing. ‘Slope: Call’ is the normalized difference between ITM Call option implied volatility and ATM Call option implied volatility; ‘Slope: Put’ is the normalized difference between OTM Put option implied volatility and ATM Put option implied volatility.



### III. Results and Discussion

Table 7a. Results for the slopes at open

|                                   | Slope                 | Slope*                | Put OTM Slope         | Call ITM Slope        |
|-----------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Unex. Traffic congestion          | 0.0609**<br>(0.0308)  | 0.0573*<br>(0.0305)   | 0.0499*<br>(0.0255)   | 0.0675<br>(0.0511)    |
| Precipitation 6 am                | -0.0036**<br>(0.0018) | -0.0030*<br>(0.0017)  | -0.0016<br>(0.0013)   | -0.0047<br>(0.0035)   |
| Visibility 9 am                   | -0.0009<br>(0.0018)   | -0.0019<br>(0.0018)   | 0.0003<br>(0.0014)    | -0.0028<br>(0.0030)   |
| Cloudiness 9am                    | -0.0021<br>(0.0014)   | -0.0028*<br>(0.0014)  | -0.0026**<br>(0.0013) | -0.0028<br>(0.0024)   |
| Temperature 9 am                  | -0.0015*<br>(0.0008)  | -0.0010<br>(0.0008)   | -0.0005<br>(0.0006)   | -0.0023<br>(0.0014)   |
| Lagged dependent                  | 0.0617<br>(0.0653)    | 0.0440<br>(0.0566)    | -0.0685<br>(0.0854)   | -0.0089<br>(0.0670)   |
| Lagged US slope                   | 0.0040<br>(0.0321)    | 0.0052<br>(0.0321)    | 0.0257<br>(0.0217)    | -0.0206<br>(0.0554)   |
| Lagged RTS futures trading volume | 0.0077<br>(0.0124)    | 0.0049<br>(0.0107)    | -0.0022<br>(0.0082)   | 0.0122<br>(0.0204)    |
| Lagged RTSVX                      | 0.0015<br>(0.0010)    | 0.0015*<br>(0.0009)   | 0.0006<br>(0.0008)    | 0.0024<br>(0.0015)    |
| Lagged VIX                        | -0.0014<br>(0.0017)   | -0.0003<br>(0.0016)   | 0.0034***<br>(0.0013) | -0.0052*<br>(0.0029)  |
| Lagged RTS futures return         | 0.0542<br>(0.2402)    | 0.0650<br>(0.2326)    | 0.1898<br>(0.1891)    | -0.0411<br>(0.4303)   |
| Lagged S&P 500 return             | 1.5504***<br>(0.4891) | 1.5540***<br>(0.4560) | 0.9988*<br>(0.5331)   | 2.3797***<br>(0.8368) |
| Time to expiration                | -0.0042<br>(0.0066)   | 0.0026<br>(0.0065)    | -0.0003<br>(0.0050)   | -0.0060<br>(0.0112)   |
| Time to exp. Sq.                  | 0.0000<br>(0.0001)    | -0.0001<br>(0.0001)   | -0.0000<br>(0.0001)   | 0.0000<br>(0.0002)    |
| Trade- but not working day        | 0.0203<br>(0.0388)    | 0.0119<br>(0.0405)    | 0.0143<br>(0.0206)    | 0.0229<br>(0.0676)    |
| Before holiday                    | 0.0013<br>(0.0139)    | -0.0008<br>(0.0120)   | -0.0028<br>(0.0134)   | 0.0001<br>(0.0286)    |
| After holiday                     | 0.0591**<br>(0.0269)  | 0.0363<br>(0.0289)    | 0.0096<br>(0.0198)    | 0.0952**<br>(0.0418)  |
| Intercept (25 <sup>th</sup> week) | 0.0805<br>(0.1967)    | 0.0023<br>(0.1758)    | 0.0667<br>(0.1589)    | 0.1518<br>(0.3027)    |
| Week effects                      | Y[9]                  | Y[5]                  | Y [10]                | Y [8]                 |
| R2                                | 0.24                  | 0.22                  | 0.28                  | 0.21                  |
| Observations                      | 433                   | 487                   | 475                   | 445                   |

The table presents results of regressions of a dependent variable on the unexpected traffic congestion and controls. Column heading presents the dependent variable for the corresponding regression. Thereby ‘Slope’ denotes the normalized difference between categories 2 and 3, as in Eq. 5, whereby the implied volatility for a category is dropped if one of the two components is missing; ‘Slope\*’ is calculated analogically (Eq. 5), but

uses non-missing implied volatility as the volatility for the category, if one of the two IVs in the category is missing. ‘Slope: Call’ is the normalized difference between ITM Call option implied volatility and ATM Call option implied volatility; ‘Slope: Put’ is the normalized difference between OTM Put option implied volatility and ATM Put option implied volatility. Explanatory variables are described in Table 2. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. We report the number of week-of-the-year effects, significant at the 10% level in square brackets. \*\*\*, \*\*, \* denote significance on the 1%, 5% and 10% level respectively.

We run regressions for the slope of the IVF, measured at open and at close of the main trading session, see Tables 7a and 7b.

For the open we find that previous period S&P return leads to a steeper slope. Also the slope is steeper after holiday (in case when we define the slope only when both IVs within each category are available). The slope seems to be negatively affected by precipitation and cloudiness (the latter – in the slope definition with using non-missing IV for the category IV). In the more restrictive definition of the slope we find also temperature having adverse effects on it, significant at the 10% level. Most importantly, traffic jams magnify the slope, this result is significant at least at the 10% level. One standard deviation higher congestion results into 84 basis points steeper slope (or about 1/9<sup>th</sup> standard deviation higher slope). This result is robust to including lagged slope at close (in the stricter slope definition it results into the decrease of significance level to 10% for the traffic variable).<sup>13</sup>

Looking at the slopes for IVs obtained from call and put options separately, one can notice that our main result holds for the slope from put options, but significance deteriorates beyond 10% for IVs from call options. One should note, that slope from put options is calculated using more liquid and frequently traded OTM options, whereas in case of calls one has to rely on less liquid and less frequently traded ITM options. Therefore our hypothesis is supported in a subsample with more observed prices, whereby the prices themselves are viewed as more reliable in the literature.

Turning to the slopes at close we observe somewhat stronger reaction to the previous day financial information: Table 7b reports significant (at 5% level for the slope) positive effect of the previous day IVF slope on the US market, previous day US volatility is significant at least at the 10% level, in some specifications lagged RTSI futures return exhibits a significant positive coefficient. In the “stricter” slope definition time to expiration seems to have an effect on slope either. More importantly, effect of the traffic jams disappears. Thus, the effect of traffic-caused stress seems to be

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<sup>13</sup> Not reported, results are available on demand

transitory, having impact on investment decisions only right after the exposure to stress. The evidence also allows to rule out some day specific effects, as the trading behavior can be observed only at open but not at close.

Table 7b. Results for the slopes at close

|                                   | Slope                | Slope*               | Put OTM Slope         | Call ITM Slope       |
|-----------------------------------|----------------------|----------------------|-----------------------|----------------------|
| Unex. Traffic congestion          | 0.0247<br>(0.0229)   | 0.0100<br>(0.0252)   | 0.0076<br>(0.0132)    | 0.0354<br>(0.0413)   |
| Precipitation 6 am                | -0.0025<br>(0.0015)  | -0.0016<br>(0.0017)  | -0.0018**<br>(0.0008) | -0.0027<br>(0.0028)  |
| Visibility 9 am                   | -0.0006<br>(0.0013)  | 0.0003<br>(0.0013)   | -0.0005<br>(0.0009)   | -0.0002<br>(0.0022)  |
| Cloudiness 9am                    | -0.0016<br>(0.0012)  | -0.0016<br>(0.0012)  | -0.0010<br>(0.0008)   | -0.0022<br>(0.0021)  |
| Temperature 9 am                  | 0.0001<br>(0.0008)   | -0.0002<br>(0.0007)  | -0.0003<br>(0.0005)   | 0.0005<br>(0.0012)   |
| Lagged dependent                  | 0.0561<br>(0.0612)   | 0.0486<br>(0.0622)   | 0.2185***<br>(0.0617) | -0.0425<br>(0.0588)  |
| Lagged US slope                   | 0.0550**<br>(0.0269) | 0.0612**<br>(0.0251) | 0.0187<br>(0.0129)    | 0.0985**<br>(0.0475) |
| Lagged RTS futures trading volume | 0.0034<br>(0.0112)   | -0.0014<br>(0.0120)  | 0.0014<br>(0.0052)    | 0.0063<br>(0.0199)   |
| Lagged RTSVX                      | 0.0004<br>(0.0008)   | -0.0005<br>(0.0007)  | 0.0000<br>(0.0005)    | -0.0001<br>(0.0012)  |
| Lagged VIX                        | 0.0023*<br>(0.0013)  | 0.0035**<br>(0.0014) | 0.0018*<br>(0.0010)   | 0.0037*<br>(0.0021)  |
| Lagged RTS futures return         | 0.3595*<br>(0.1861)  | 0.2746<br>(0.2011)   | 0.2596**<br>(0.1197)  | 0.3205<br>(0.3278)   |
| Lagged S&P 500 return             | -0.5120<br>(0.3699)  | -0.0095<br>(0.4051)  | -0.2737<br>(0.2378)   | -0.7011<br>(0.6454)  |
| Time to expiration                | 0.0126*<br>(0.0074)  | 0.0081<br>(0.0067)   | -0.0034<br>(0.0032)   | 0.0245*<br>(0.0129)  |
| Time to exp. Sq.                  | -0.0002*<br>(0.0001) | -0.0001<br>(0.0001)  | 0.0001<br>(0.0001)    | -0.0004*<br>(0.0002) |
| Trade- but not working day        | 0.0846<br>(0.0700)   | 0.0506<br>(0.0570)   | 0.0000<br>(0.0204)    | 0.1346<br>(0.1276)   |
| Before holiday                    | 0.0068<br>(0.0151)   | 0.0048<br>(0.0152)   | -0.0059<br>(0.0090)   | 0.0154<br>(0.0286)   |
| After holiday                     | 0.0243<br>(0.0331)   | 0.0380<br>(0.0336)   | -0.0071<br>(0.0137)   | 0.0577<br>(0.0573)   |
| Intercept (25 <sup>th</sup> week) | -0.2143<br>(0.1823)  | -0.0783<br>(0.1927)  | 0.0803<br>(0.0882)    | -0.4697<br>(0.3337)  |
| Week effects                      | Y[8]                 | Y[5]                 | Y [6]                 | Y [10]               |
| R2                                | 0.19                 | 0.16                 | 0.31                  | 0.15                 |
| Observations                      | 431                  | 484                  | 474                   | 440                  |

The table presents results of regressions of a dependent variable on the unexpected traffic congestion and controls. Column heading presents the dependent variable for the corresponding regression. Explanatory variables are described in Table 2. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. We report the number of week-of-the-year effects, significant at the 10% level in square brackets. \*\*\*, \*\*, \* denote significance on the 1%, 5% and 10% level respectively.

#### IV. Robustness checks

To check whether the effect at the open is not purely due to chance we regress the slope at the open on the unexpected traffic congestion in the evening of the same day (unexpected average congestion from 18:15 to 19:45, whereby the morning congestion is included into the conditioning set) – since this information is unavailable to investors at the morning, it should not affect their trading patterns.

Table 8. Results for the slopes at open, evening traffic

|                                   | Slope                 | Slope*                | Put OTM Slope         | Call ITM Slope        |
|-----------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Unex. Traffic congestion, evening | -0.0053<br>(0.0204)   | -0.0014<br>(0.0204)   | 0.0057<br>(0.0205)    | -0.0149<br>(0.0300)   |
| Precipitation 6 am                | -0.0029<br>(0.0018)   | -0.0021<br>(0.0017)   | -0.0007<br>(0.0013)   | -0.0042<br>(0.0035)   |
| Visibility 9 am                   | -0.0012<br>(0.0019)   | -0.0016<br>(0.0017)   | 0.0002<br>(0.0015)    | -0.0034<br>(0.0031)   |
| Cloudiness 9am                    | -0.0021<br>(0.0014)   | -0.0026*<br>(0.0014)  | -0.0027**<br>(0.0014) | -0.0028<br>(0.0024)   |
| Temperature 9 am                  | -0.0016<br>(0.0009)   | -0.0012<br>(0.0009)   | -0.0004<br>(0.0006)   | -0.0025<br>(0.0016)   |
| Lagged dependent                  | 0.1172*<br>(0.0691)   | 0.0981*<br>(0.0611)   | -0.0505<br>(0.0973)   | 0.0065<br>(0.0714)    |
| Lagged US slope                   | 0.0043<br>(0.0324)    | 0.0061<br>(0.0325)    | 0.0231<br>(0.0224)    | -0.0170<br>(0.0569)   |
| Lagged RTS futures trading volume | 0.0095<br>(0.0130)    | 0.0097<br>(0.0111)    | -0.0006<br>(0.0081)   | 0.0133<br>(0.0215)    |
| Lagged RTSVX                      | 0.0013<br>(0.0009)    | 0.0011<br>(0.0008)    | 0.0005<br>(0.0008)    | 0.0022<br>(0.0015)    |
| Lagged VIX                        | -0.0015<br>(0.0017)   | -0.0002<br>(0.0016)   | 0.0033**<br>(0.0014)  | -0.0052*<br>(0.0030)  |
| Lagged RTS futures return         | -0.0731<br>(0.2594)   | -0.0715<br>(0.2439)   | 0.1356<br>(0.1963)    | -0.1264<br>(0.4505)   |
| Lagged S&P 500 return             | 1.6181***<br>(0.5066) | 1.6477***<br>(0.4609) | 1.1044**<br>(0.5457)  | 2.3200***<br>(0.8735) |
| Time to expiration                | -0.0028<br>(0.0071)   | 0.0057<br>(0.0071)    | 0.0017<br>(0.0051)    | -0.0053<br>(0.0120)   |
| Time to exp. Sq.                  | 0.0000<br>(0.0001)    | -0.0001<br>(0.0001)   | -0.0000<br>(0.0001)   | 0.0000<br>(0.0002)    |

|                                   |                     |                     |                     |                     |
|-----------------------------------|---------------------|---------------------|---------------------|---------------------|
| Trade- but not working day        | -0.0028<br>(0.0400) | 0.0073<br>(0.0433)  | -0.0028<br>(0.0180) | -0.0074<br>(0.0693) |
| Before holiday                    | -0.0048<br>(0.0171) | -0.0025<br>(0.0141) | -0.0068<br>(0.0136) | -0.0046<br>(0.0324) |
| After holiday                     | 0.0523*<br>(0.0296) | 0.0322<br>(0.0322)  | 0.0061<br>(0.0212)  | 0.0858*<br>(0.0448) |
| Intercept (25 <sup>th</sup> week) | 0.0438<br>(0.1957)  | -0.1046<br>(0.1804) | 0.0217<br>(0.1528)  | 0.1377<br>(0.3145)  |
| Week effects                      | Y[6]                | Y[9]                | Y [8]               | Y [7]               |
| R2                                | 0.25                | 0.23                | 0.30                | 0.21                |
| Observations                      | 417                 | 467                 | 455                 | 429                 |

The table presents results of regressions of a dependent variable on the unexpected traffic congestion and controls. Column heading presents the dependent variable for the corresponding regression. Thereby ‘Slope’ denotes the normalized difference between categories 2 and 3, as in Eq. 5, whereby the implied volatility for a category is dropped if one of the two components is missing; ‘Slope\*’ is calculated analogically (Eq. 5), but uses non-missing implied volatility as the volatility for the category, if one of the two IVs in the category is missing. ‘Slope: Call’ is the normalized difference between ITM Call option implied volatility and ATM Call option implied volatility; ‘Slope: Put’ is the normalized difference between OTM Put option implied volatility and ATM Put option implied volatility. Explanatory variables are described in Table 2. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. We report the number of week-of-the-year effects, significant at the 10% level in square brackets. \*\*\*, \*\*, \* denote significance on the 1%, 5% and 10% level respectively.

Results of this robustness checks in Table 8 yield no significant influence of future traffic shocks on the slope of IVF at open, whereby all the controls behave similarly to our base regression (Table 7a). Thus, we find support of our original results not being obtained due to mere chance.

## **V. Conclusion**

This paper studies the role of stress induced by time constraints on investors' decision making. Arguably, the immediacy of trading decisions thrusts floor traders to integrate system-1 and system-2 processes into their decision making tasks. Moreover, the need to perform contemporaneous tasks and external interference such as arriving unexpectedly late to work, might exacerbate acute stress and its impact on decision making.

Accumulated laboratory research suggests that time stress may impact financial decisions, mainly in the loss domain. The goal of our research is to study this issue in real financial markets, because: (i) in markets, people are confronted with repeated situations and have the opportunity to learn from their own and others' experience; (ii) lab results might not carry over to the market because market prices are aggregate outcomes in which individual violations of rationality may be washed out; (iii) individuals may apply different decision rules when they are confronted with real-life situations; and (iv) decisions in real-life financial markets involve extremely high monetary stakes.

We use data on traffic congestion, weather conditions and stock and derivatives. The main dependent variable we employ is the slope of the implied volatility function (IVF) of options on RTS futures (cf. Bollen and Whaley, 2004) at the left-hand side of the volatility smile (corresponding to the loss domain). We find that, controlling for relevant factors, this slope at open of the main trading session is higher subsequent to morning traffic jams, suggesting that investors under stress assign higher weights to extreme loss scenarios.

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