Trading Dynamics in the Foreign Exchange Market
A Latent Factor Panel Intensity Approach

Ingmar Nolte †
Warwick Business School, FERC, CoFE

Valeri Voev‡
University of Aarhus, CREATES

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†Warwick Business School, Finance Group, Coventry, CV4 7AL, United Kingdom. Phone +44-24765-72838, Fax -23779, email: Ingmar.Nolte@wbs.ac.uk.
‡CREATES, School of Economics and Management, University of Aarhus, 8000 Aarhus C, Denmark Phone +45-8942 1539, email: vvoev@creates.au.dk. The Center for Research in Econometric Analysis of Time Series, CREATES, is funded by The Danish National Research Foundation.
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Abstract

We develop a panel intensity framework for the analysis of complex trading activity datasets containing detailed information on individual trading actions in different securities for a set of investors. A feature of the model is the presence of a time varying latent factor, which captures the influence of unobserved time effects and allows for correlation across individuals. We show how to estimate the model parameters using a simulated maximum likelihood technique adopting the efficient importance sampling approach of Richard & Zhang (2007).

Apart from the innovative methodology enabling detailed characterization of a complex dynamic trading process, we contribute to the literature on behavioral finance by providing new results on behavioral biases such as the disposition effect and investor overconfidence. These new insights are made possible by the joint characterization of not only the decision to close (exit) a position, usually considered in isolation in the behavioral finance literature, but also the decision to open (enter) a position, which together describe the trading process in its entirety. While the disposition effect is defined with respect to the willingness to realize profits/losses with respect to the performance of the position under consideration, we find that the performance of the total portfolio of positions is an additional factor influencing trading decisions and can reinforce or dampen the standard disposition effect. Moreover, the proposed methodology allows the investigation of the severity of various behavioral biases for different groups of investors ranging from small retail investors to professional and institutional investors.

**JEL classification:** C3, C5, G1

**Keywords:** Trading Activity Datasets, Panel Intensity Models, Latent Factors, Efficient Importance Sampling, Behavioral Finance
1 Introduction

The complexity of financial market data containing micro-information on every individual trader’s action presents new challenges to financial economists and econometricians. The immense breadth of this data opens new horizons for the analysis of market microstructure and behavior of economic agents, beyond the analyses possible with standard high frequency data which has led to the birth of high-frequency finance as a new research area focusing on issues such as irregularly spaced and discrete data, volatility measurement and market microstructure.

Trading activity datasets now becoming increasingly available, can be considered as micro-panel datasets with four dimensions: an irregularly-spaced time scale, types of trading actions, trading instruments and investors. The marvelous amount of precise information contained in these datasets creates unique possibilities to analyze individual trading behavior since the investment patterns of each individual in multiple assets can be followed over time. Time plays a central role in high-frequency finance, market microstructure and the behavioral finance literature. Trading activity datasets can be considered as field data with exact information on the timing of investment decisions hence enabling in-depth investigations of prominent behavioral finance phenomena such as the disposition effect as well as the motives driving investment decisions at specific points in time. Investors are typically heterogenous with respect to their trading and risk preferences and trading activity datasets provide a sound data fundament for the detailed investigation of trading behavior for different groups of investors from small retail to professional and institutional investors.

In this paper we develop an intensity-based modelling framework which is suited to characterize the data generating process of complex dynamic systems such as trading activity datasets. Time is considered as the central element in the model enabling the investigation of those factors that influence trading decisions of investors in multiple assets over time. The model exploits the panel structure of the trading activity dataset and characterizes a multivariate panel intensity process which is specified as a function of individual specific effects, a dynamic component, a set of time varying covariates describing the investors’ information set, a seasonality component and a time-varying latent factor. The latent factor is motivated by the fact that not all individual-specific as well as public information is directly observable or measurable with available explanatory variables. These omitted unobservable factors induce dependencies across individuals which are captured by the common latent factor. The intensity based specification is chosen, since it allows us to account for the impact of
time-varying covariates on the trading process. We use a simulated maximum likelihood (SML) technique to estimate the proposed model by augmenting the efficient importance sampling (EIS) method of Richard & Zhang (2007) for the estimation of panel intensity models. Our approach is related to the stochastic conditional intensity (SCI) model proposed by Bauwens & Hautsch (2006) which they use to characterize a system of duration processes. The model we propose here differs from the SCI model by considering a panel intensity model which in terms of its complexity allows for two additional dimensions: individuals and trading instruments. Such degree of complexity is required in order to jointly model all aspects of a trading activity dataset, and thus provides a framework for considering individual- and transaction type-specific effects.

The model is applied to the analysis of the trading behavior of investors in the foreign exchange market based on a trading activity dataset of OANDA FXTrade, which allows us to trace every action of around 2500 investors in up to 30 currency pairs over the period from 1st October 2003 to 31st October 2003. OANDA FXTrade is an electronic trading platform in the foreign exchange market, in which heterogeneous groups of small retail investors as well as big institutional and professional traders are active. Our analysis focuses on two well investigated behavioral finance biases, the disposition effect and overconfidence. The disposition effect (Shefrin & Statman (1985)) describes the tendency to hold positions with a paper loss longer than positions with the symmetric paper profit. A theoretical foundation for the disposition effect is given by the prospect theory of Kahneman & Tversky (1979), in which the investor evaluates the outcome of a trading strategy relative to a reference point and is risk averse if the strategy is profitable with respect to that reference point and risk seeking otherwise. The early studies of Lease, Lewellen & Schlarbaum (1974), Schlarbaum, Lewellen & Lease (1978a,b), Shefrin & Statman (1985) as well as the more recent contributions of Badrinath & Lewellen (1991), Locke & Mann (2005) and Shapira & Venezia (2001) analyze the disposition effect by comparing mean roundtrip durations of profitable and non-profitable investments. Odean (1998a) considers the proportions of profits and losses realized over a certain time horizon and Grinblatt & Keloharju (2001) apply ordered response models for the analysis of the disposition effect. Most of these studies examine the disposition effect isolated for trading in a specific security in a static framework for the average investor. The studies by Shapira & Venezia (2001), Dhar & Zhu (2006), Goetzmann & Massa (2004) and Chen, Kim, Nofsinger & Rui (2007) focus on investor heterogeneity and show that professional and more sophisticated investors are less prone to the disposition effect and to behavioral biases.
in general.

Overconfidence is a further phenomenon highlighted in the behavioral finance literature. It can be explained by self-attribution bias (Wolosin, Sherman & Till (1973)) caused by overly self-confident interpretations of past (trading) success, and biased perceptions of the precision and validity of private information and predictions (Alpert & Raiffa (1982), Lichtenstein, Fischhoff & Phillips (1982)). In the literature overconfidence has been suggested as an explanation for the unusually high observed volume in security trading. Theoretical models which yield this conclusion have been developed by Daniel, Hirshleifer & Subrahmanyam (1998), Odean (1998b), Wang (1998), Gervais & Odean (2001) and Scheinkman & Xiong (2003). Empirical evidence is provided by for instance, the studies of De Bondt & Thaler (1995), Barber & Odean (2001a), Statman, Thorley & Vorkink (2006) on the basis of monthly data.

In our analysis we find support for the existence of the disposition effect and overconfidence which is in line with numerous theoretical and empirical studies. The originality of our approach lies in adopting a more general perspective in analyzing trading behavior, by addressing directly the timing of investment decisions at the micro-level, which is central to the understanding of the dynamics of trading. Categorizing our investors into groups according to their total trading volume allows us to draw conclusions on the severity of different behavioral biases and differences in the trading behavior across various types of investors. We explicitly model both the propensity to open and close positions, allowing us to obtain a complete picture of investment decisions. The empirical analysis reveals new results on the disposition effect in conjunction with the prospect theory and delivers insights into further behavioral biases related to the usual disposition effect.

The paper is structured as follows: in Section 2 we provide a theoretical description of the model. Section 3 contains the empirical analysis, Section 4 discusses the results in light of recent behavioral finance and market microstructure theories and Section 5 concludes. A detailed exposition of the SML estimation procedure is presented in Appendix A and the full estimation results are collected in Appendix B.

2 Panel Intensity Model

2.1 Theory

Let $t \in [0, T]$ denote the physical calendar time, $n = 1, \ldots, N$ denote the $n^{th}$ investor and $k = 1, \ldots, K$ denote the $k^{th}$ currency pair in which an investor can trade. The $i^{th}$
The likelihood function of the complete model without a latent factor is given by

\[ d \text{all relevant parameters used in the estimation. By } t \text{ we denote the filtration, which consists of all information up to but excluding time } f \text{ where } \{ \tau_i \mid 0 \leq \tau_i \leq T; i = 1, \ldots, I^{k,n} \} \text{ represent point processes with corresponding right-continuous counting processes } N_i^{k,n}(t) = \sum_{i=1}^{I^{k,n}} 1_{(\tau_i^{k,n} < t)} \text{ which count the number of actions in the time interval } [0, t]. \text{ The corresponding left-continuous counting process is denoted by } \tilde{N}_i^{k,n}(t) = \sum_{i=1}^{I^{k,n}} 1_{(\tau_i^{k,n} < t)}. \text{ Let } \{ \Omega, \mathcal{F}, \mathcal{F}_t, \mathcal{P} \} \text{ denote the associated joint probability space, where the filtrations of the individual processes are denoted by } \mathcal{F}_i^{k,n} \subset \mathcal{F}_t. \text{ We assume that each individual point process is orderly (simple), ensuring that there are no simultaneous arrivals and implying that } \tau_i^{k,n} < t_i^{k,n} (\text{almost surely}), \text{ for } i = 1, \ldots, I^{k,n}. \text{ The inter-event duration between two consecutive actions is denoted by } \tau_i^{k,n} = t_i^{k,n} - t_{i-1}^{k,n}. \text{ } u^{k,n}(t) = t - N_i^{k,n}(t) \text{ denotes the corresponding backward recurrence time at } t \text{ measuring the elapsed time since the last event. For each investor and for each currency pair the arrival times } \{ t_i^{k,n} \mid i = 1, \ldots, I^{k,n} \} \text{ constitute a pooled process, induced by } S \text{ sub-processes. The corresponding arrival times of the } s^{th} \text{ sub-process are denoted by } t_i^{s,k,n} \text{ with } i = 1, \ldots, I^{s,k,n}. \text{ Since the pooled process is orderly the sub-processes are orderly as well. Defining } N_i^{s,k,n}(t) = \sum_{i=1}^{I^{s,k,n}} 1_{(t_i^{s,k,n} < t)} \text{ as the corresponding counting functions we have that } N_i^{k,n}(t) = \sum_{n=1}^{S} N_i^{s,k,n}(t). \text{ In our application we observe } S = 2 \text{ sub-processes which are:}

- \text{ } s = 1: \text{ The process related to an increase in a given currency pair exposure, i.e., the process characterizing the (further) opening of a position;}
- \text{ } s = 2: \text{ The process related to a decrease in a given currency pair exposure, i.e., the process characterizing the (partial) closing of a position.}

The likelihood function of the complete model without a latent factor is given by

\[
\mathcal{L}(W; \theta) = \prod_{n=1}^{N} \prod_{k=1}^{K} \left( \prod_{i=1}^{I^{k,n}} f_i^{k,n}(\tau_i^{k,n} \mid \mathcal{F}_i^{k,n}) \right)^{d_n^k},
\]

where \( f_i^{k,n}(\tau_i^{k,n} \mid \mathcal{F}_i^{k,n}) \) is the conditional density function of the durations. With \( \mathcal{F}_i^{k,n} \) we denote the filtration, which consists of all information up to but excluding time \( t_i^{k,n} \). \( W \) denotes the generic symbol for all relevant data and \( \theta \) is the generic symbol for all relevant parameters used in the estimation. By \( d_n^k \) we denote the dummy variable.

\(^1\)By action we refer to any event that changes the investor’s portfolio value. Thus, it can be initiated by the investor at that particular time or be a consequence of an earlier activity of the investor, e.g., an executed limit order.

\(^2\)i.e. \( P(N_i^{k,n}(t + \delta) > N_i^{k,n}(t) \mid \mathcal{F}_i^{k,n}) = o(\delta) \), with \( o(\cdot) \) the little Landau symbol.
which takes on the value 1 if the $n^{th}$ investor is active in currency pair $k$ at least once, and zero otherwise.

We can write the conditional probability of the duration $t_{i}^{k,n}$ between two arbitrary consecutive actions as the conditional probability that all processes have survived during the period $[t_{i-1}^{k,n}, t_{i}^{k,n}]$ times the instantaneous probability for arrival in the next instant $t_{i}^{k,n}$, which is formally given by

$$f^{k,n}(t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) = \prod_{s=1}^{S} F^{s,k,n}(t_{i-1}^{k,n}, t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) \left( \bar{\Theta}^{s,k,n}(t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) \right) d_{i}^{s,k,n}, \quad (2)$$

where $d_{i}^{s,k,n}$ is a dummy, which takes on the value of one whenever the duration ends with an arrival of type $s$, and zero otherwise. $F^{s,k,n}$ denotes the “survivor” function of the $s$-type process given by

$$F^{s,k,n}(t_{i-1}^{k,n}, t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) = P \left( t_{N^{s,k,n}(t_{i-1}^{k,n})+1}^{s,k,n} \notin \left[ t_{i-1}^{k,n}, t_{i}^{k,n} \right), t_{N^{s,k,n}(t_{i-1}^{k,n})+1}^{s,k,n} = t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n} \right), \quad (3)$$

which is the joint probability that there is a $s$-type event at time $t_{i}^{k,n}$ but not during the period from $t_{i-1}^{k,n}$ to $t_{i}^{k,n}$. The corresponding intensity of type $s$ is denoted by

$$\bar{\Theta}^{s,k,n}(t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) = \lim_{h \to 0} \frac{P \left( t_{i}^{k,n} \leq t_{N^{s,k,n}(t_{i-1}^{k,n})+1}^{s,k,n} < t_{i}^{k,n} + h \mid t_{N^{s,k,n}(t_{i-1}^{k,n})+1}^{s,k,n} \notin \left[ t_{i-1}^{k,n}, t_{i}^{k,n} \right), \bar{\Theta}_{i}^{k,n} \right)}{h}, \quad (4)$$

which is the instantaneous probability for a $s$-type event at time $t_{i}^{k,n}$. It follows that

$$F^{s,k,n}(t_{i-1}^{k,n}, t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) = \exp \left( -\int_{t_{i-1}^{k,n}}^{t_{i}^{k,n}} \bar{\Theta}^{s,k,n}(u \mid \bar{\Theta}_{i}^{k,n}) \, du \right) = \exp \left( -\Theta^{s,k,n}(t_{i-1}^{k,n}, t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) \right),$$

where $\Theta^{s,k,n}(t_{i-1}^{k,n}, t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n})$ denotes the $s$-type integrated intensity between $t_{i-1}^{k,n}$ and $t_{i}^{k,n}$. Therefore, the likelihood function of the model without a latent factor in equation (1) can be rewritten as

$$L(W; \theta) = \prod_{n=1}^{N} \prod_{k=1}^{K} \prod_{i=1}^{S} F^{s,k,n}(t_{i-1}^{k,n}, t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) \left( \bar{\Theta}^{s,k,n}(t_{i}^{k,n} \mid \bar{\Theta}_{i}^{k,n}) \right) d_{i}^{s,k,n}. \quad (5)$$
Since we believe that investors’ behavior is influenced by unobservable time varying factors, we introduce a latent factor denoted by $\lambda_i$. To model the dynamic behavior of the latent factor, we need to introduce a time scale over which the latent factor evolves. To this end, we define the ordered pooled point process as the sequence of arrival times $t_i, i = 1, \ldots, I$ for all actions of all investors in all currency pairs, where simultaneous arrivals are treated as one arrival only. The corresponding counting processes are denoted by $N(t) = \sum_{i=1}^{I} 1_{\{t_i \leq t\}}$ and $\tilde{N}(t) = \sum_{i=1}^{I} 1_{\{t_i < t\}}$. Thus, for $t \in \{t_i\}$ we have $N(t) = \tilde{N}(t) + 1$, whereas for $t \notin \{t_i\}$ it holds that $N(t) = \tilde{N}(t)$.

The pooled process $\{t_i\}_{i=1}^{I}$ serves as the time scale on which the latent factor evolves. In particular, we assume that the duration $\tau_{N,k,n}^{k,n}(t)$ depends on the latent factor, i.e. $\tau_{N,k,n}^{k,n}(t) = \tau_{N,k,n}^{k,n}(\lambda_{\tilde{N}(t)+1})$ at $t \in \bigcup_n \bigcup_k \{t_i \}$. Note that this definition ensures that at every time $t$ at which an action occurs, there is a corresponding value of the latent factor. Here, the latent factor is assumed to evolve over a kind of irregularly spaced event induced time scale, while alternatively we could choose an equidistant time grid. In order to summarize and visualize the model specification, data characteristics, and in particular the different time scales we depict the stylized panel structure in Figure 1. In the figure, we allow for the presence of time varying covariates for each subprocess $s$. The time scales over which these covariates evolve, will be defined below.

Since the latent factor is unobservable and stochastic it needs to be integrated out, which results in the following likelihood function

$$L(W; \theta) = \int_{\mathbb{R}^I} \prod_{n=1}^{N} \prod_{k=1}^{K} \prod_{i=1}^{I} f^{k,n}(\tau_{i}^{k,n}, \lambda_{\tilde{N}(t_i^{k,n})+1} | \tilde{\mathcal{F}}_{t_i^{k,n}}^{k,n}) d\lambda,$$

where $\Lambda = (\lambda_1, \ldots, \lambda_I)'$ and the integral is taken over $\mathbb{R}^I$, and where $f^{k,n}(\tau_{i}^{k,n}, \lambda_{\tilde{N}(t_i^{k,n})+1} | \tilde{\mathcal{F}}_{t_i^{k,n}}^{k,n})$ is the joint conditional density of the duration $\tau_{i}^{k,n}$ and its corresponding latent factor $\lambda_{\tilde{N}(t_i^{k,n})+1}$. The likelihood can then be factored as the product of the density

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*Formally,*

$$\{t_i | t_i-1 < t_i\} = \bigcup_n \left\{ \bigcup_k \{t_i^{k,n} | t_i-1^{k,n} < t_i^{k,n} \} \right\} \cap \left\{ \bigcup_k \{t_i^{k,n} | t_i-1^{k,n} < t_i^{k,n} \} \right\}.$$
Figure 1: Stylized Model Structure. The figure represents for $s = 2$ the time scales associated with the arrival times of the processes (sub-pr.1 and sub-pr.2), the times of the covariate processes (cov.1 and cov.2) as well as the pooled arrival processes $\tilde{t}_{h,k,n}^{1}$ and $t_{i}^{k,n}$. 

Stylized Panel Structure

$N$ investors, $K$ currency pairs, $S$ sub-processes
conditional on the latent factor times the conditional density of the latent factor as

\[ L(W; \theta) = \int_{\mathbb{R}^t} \prod_{n=1}^N \prod_{k=1}^K \prod_{s=1}^S F_{s,k,n} \left( t_{i-1}^{k,n}, t_i^{k,n}, \theta \right) \]

\[ \left( \vartheta_{s,k,n} \left( t_i^{k,n}, \lambda_i \right) \right) d\vartheta_{s,k,n} \rho \left( \lambda_i \mid t_i^{k,n} \right) d\lambda_i, \]  

where \( \rho \left( \lambda_i \mid t_i^{k,n} \right) \) is the conditional density of the latent factor. The exact specification of the intensities and the corresponding integrated intensities is presented below.

The model described by the likelihood function in equation (7) is formulated in terms of \( t_i^{k,n} \), which is the pooled (orderly) point process over the \( S \) subprocesses of the \( n \)th investor in the \( k \)th currency pair. As the latent factor which has to be integrated out is defined on \( t_i \), we also provide a reformulation of the likelihood in equation (7) in terms of the pooled times \( t_i \), which eases the implementation of the EIS estimation algorithm described in detail in Appendix A. Since the pooled process may not be orderly, there may be several pairs \( (k, n) \) associated with the arrival time \( t_i \), i.e., several investors trading at the same time and/or the same investor trading in different currency pairs at the same time. We denote the set of such pairs by \( C_i = \{(k, n) \mid t_i^{k,n} = t_i \} \). The likelihood in (7) can then be rewritten as

\[ L(W; \theta) = \int_{\mathbb{R}^t} \prod_{i=1}^I \prod_{s=1}^S F_{s,k,n} \left( t_{N_k,n(t_i)}^{k,n}, t_i^{k,n}, \theta \right) \]

\[ \left( \vartheta_{s,k,n} \left( t_i^{k,n}, \lambda_i \right) \right) d\vartheta_{s,k,n} \rho \left( \lambda_i \mid t_i^{k,n} \right) d\lambda_i. \]  

As suggested by the model presentation above, there are several ways to model the likelihood function. One can either specify the likelihood function \( \mathcal{L} \) for the durations of the pooled process \( t_i^{k,n} \) directly, or the likelihood function \( \mathcal{L} \) based on the intensities of the \( s \) sub-processes \( t_i^{s,k,n} \) which generate the pooled process \( t_i^{k,n} \). Although in different ways, both approaches ultimately allow for inference on the durations \( \tau_i^{k,n} \) of the pooled process.

An attractive feature of intensity based modelling is that it accounts for changes in the values of time varying covariates during a duration in a very intuitive way since it is set up in continuous time. The duration based approach, which is a discrete time model can also account for time varying covariates (e.g., Lunde & Timmermann (2005)), but then the likelihood function has to be additionally adjusted (effectively this again amounts to adjusting the intensity to reflect the changes in the values of
the covariates). Furthermore, the intensity based approach allows for the characterization of the dynamic behavior of each of the $s$ sub-processes, whereas the duration approach considers the pooled process only. One possibility for modelling the duration based likelihood (6) is to adopt the stochastic conditional duration (SCD) approach of Bauwens & Veredas (2004), whereas likelihood (7) can be modelled by augmenting the stochastic conditional intensity (SCI) model of Bauwens & Hautsch (2006). We rely on the latter strategy and parameterize $\theta^{s,k,n}(t|\mathcal{F}_t^{-1}, \lambda_{N(t)+1})$ generally in the following way:

$$
\theta^{s,k,n}(t|\mathcal{F}_t^{-1}, \lambda_{N(t)+1}) = \left( b^{s,k,n}(t)S^{s,k,n}(t)\Psi^{s,k,n}(t|\mathcal{F}_t^{-1})(\lambda_{N(t)+1})^{\delta^{s,k,n}} \right) D^{s,k,n}(t). 
$$

Thereby $b^{s,k,n}(t)$ denotes a (possibly investor, currency pair or state dependent) baseline intensity, $S^{s,k,n}(t)$ – a deterministic seasonality function, $\Psi^{s,k,n}(t|\mathcal{F}_t^{-1})$ – an intensity component capturing the dynamic information processing, and $\delta^{s,k,n}$ is a parameter which controls for the impact of the latent component on the $s$-type intensity. In our application we need to take into account that after an action which sets the exposure in a given currency pair to zero, i.e. the position is closed completely, there is no possibility for a subsequent close. Hence, the intensity $\theta^{2,k,n}(t|\mathcal{F}_t^{-1}, \lambda_{N(t)+1})$ is zero in this case. We model this through the variable

$$
D^{s,k,n}(t) = \begin{cases} 
1 & \text{if } s = 1 \\
1 - d^{k,n}(t) & \text{if } s = 2,
\end{cases}
$$

where $d^{k,n}(t)$ denotes the dummy variable which takes on the value 1, if the previous arrival time is associated with a complete close of the position in the currency pair $k$ for investor $n$, and zero otherwise.

### 2.2 Model Parametrization

For the application we will parameterize the separate intensity components parsimoniously in the following way:

**Baseline Intensity & Individual Investor Specific Effects**

We assume that there are different baseline intensities for the different states and the individual investors, but that they are identical across currency pairs. That is we assume that

$$
b^{s,k,n}(t) = b^{s,n}(t) \quad \text{for } k = 1, \ldots, K \text{ and } n = 1, \ldots, N.
$$
In the application we use a multivariate Weibull specification of the following form:

$$b_{s,n}^n(t) = \exp(\omega_n^n) \prod_{r=1}^S u_{r,n}^r(t)^{\alpha_n^r-1} \quad \text{for } s = 1, \ldots, S,$$

where the location parameters $\omega_n^n$ are investor $n$ and state $s$ specific and the shape parameters $\alpha_n^s$ are assumed to be identical for all investors, but different across states. Thus, the individual investor effect allows for investor specific shifts of the intensity specification.

**Diurnal Seasonality and Weekend Effects**

The seasonality function $S_{s,k,n}^s(t)$ incorporates a diurnal seasonality component $\tilde{S}_{s,k,n}(t)$ and a weekend component $\tilde{W}_{s,k,n}(t)$ multiplicatively as

$$S_{s,k,n}^s(t) = \tilde{S}_{s,k,n}(t) \tilde{W}_{s,k,n}(t).$$

In order to capture the deterministic intraday seasonality pattern of the intensity processes we assume that

$$\tilde{S}_{s,k,n}(t) = \tilde{S}(t) \quad \text{for } k = 1, \ldots, K \text{ and } n = 1, \ldots, N.$$  

where

$$\tilde{S}(t) \equiv \tilde{S}(\nu, \tau(t), K) \equiv \exp \left( \nu_0 \tau(t) + \sum_{k=1}^K \nu_{2k-1} \sin(2\pi(2k-1)\tau(t)) + \nu_{2k} \cos(2\pi(2k)\tau(t)) \right)$$

which is an exponentially transformed Fourier flexible form with linear intraday time trend, where $\tau(t)$ denotes the intraday trading time standardized to $[0, 1]$ and $\nu$ is a $2K + 1$ dimensional parameter vector. To model the lower degree of trading activity on weekends, we specify $\tilde{W}(t)$ as

$$\tilde{W}(t) = \exp(\varpi D_W(t)),$$

where $\varpi$ denotes a scalar and $D_W(t)$ a weekend dummy, which is one during weekends and zero otherwise. According to this specification the intensity process is dampened for $\varpi < 0$, which is the effect that we expect, and amplified for $\varpi > 0$. Note that the seasonality component is neither state, currency nor investor specific, which is partly driven by the fact that we do not empirically observe large differences in the intra-day seasonality pattern for open and close arrival times and specific investor types (see Section 3) and by the fact that we want to obtain a parsimonious set of parameters.
Dynamics and Explanatory Variables

The dynamic structure and the influence of the explanatory variables is modelled through $\Psi^{s,k,n}(t|\mathcal{F}_t)$ in the autoregressive conditional intensity (ACI) fashion suggested by Russell (1999). Let $z^{s,k,n}_j$ denote the vector of all (time-varying) possibly investor, currency pair and state dependent covariates, where at least one covariate is updated at time $\tilde{t}^{s,k,n}_j$ with $j = 1, \ldots, J^{s,k,n}$. $M^{s,k,n}(t) = \sum_{j=1}^{J^{s,k,n}} 1_{\{\tilde{t}^{s,k,n}_j < t\}}$ is the corresponding left continuous counting function of the update times $\tilde{t}^{s,k,n}_j$. Furthermore, let $\{\tilde{t}^{s,k,n}_h\}$ denote the process resulting from the pooling of the process $\{t_i\}$ and the covariate process $\{\tilde{t}^{s,k,n}_j\}$, with $H^{s,k,n}(t) = \sum_{h=1}^{H^{s,k,n}} 1_{\{\tilde{t}^{s,k,n}_h \leq t\}}$ denoting the corresponding right continuous counting function. We assume that

$$\Psi^{s,k,n}(t|\mathcal{F}_{-t}) = \exp\left(\tilde{\Psi}^{s,k,n}_{\tilde{N}^{s,k,n}(t) + 1} + (z^{s,k,n}_{\tilde{M}^{s,k,n}(t)})' \gamma^{s,k,n}\right).$$

Note that $\tilde{\Psi}^{s,k,n}$ is indexed by $\tilde{N}^{s,k,n}(t) + 1$, which ensures that $\tilde{\Psi}^{s,k,n}$ is updated with the value of $\tilde{\Psi}^{s,k,n}_i$ directly after but excluding $\tilde{t}^{s,k,n}_i - 1$ and stays constant until and including $\tilde{t}^{s,k,n}_i$. The coefficient vector is denoted by $\gamma^{s,k,n}$. The vector $\tilde{\Psi}^{k,n}_i = (\tilde{\Psi}^{1,k,n}_i, \ldots, \tilde{\Psi}^{S,k,n}_i)'$ is parametrized multivariately as

$$\tilde{\Psi}^{k,n}_i = \sum_{s=1}^{S} \left( A^{s,k,n} \varepsilon^{k,n}_{i-1} + B^{k,n} \tilde{\Psi}^{k,n}_{i-1} \right) \tilde{t}^{s,k,n}_{i-1},$$

where generally $A^{s,k,n}$ is an $S \times 1$ parameter vector and $B^{k,n}$ is an $S \times S$ parameter matrix. In the application we assume that $A^{s,k,n} \equiv A^s$ is state but not investor and currency specific and that $B^{k,n} \equiv B$ does also not depend on the individual investor or the currency pair. Moreover, we restrict $B$ to be diagonal. The innovation term $\varepsilon^{k,n}_i$ is given by

$$\varepsilon^{k,n}_i = \sum_{s=1}^{S} \tilde{t}^{s,k,n}_{i-1} \varepsilon^{s,k,n}_i,$$

where

$$\varepsilon^{s,k,n}_i = -0.5772 - \ln \Theta^{s,k,n} \left( t^{s,k,n}_{i-1}, t^{s,k,n}_i | \tilde{\mathcal{F}}_{t^{s,k,n}_i}, \lambda_{\tilde{N}(t^{s,k,n}_i + 1)} \right), \quad (11)$$

in which the integrated intensity is computed as

$$\Theta^{s,k,n} \left( t^{s,k,n}_{i-1}, t^{s,k,n}_i | \tilde{\mathcal{F}}_{t^{s,k,n}_i}, \lambda_{\tilde{N}(t^{s,k,n}_i + 1)} \right) =$$

$$\sum_{h=H^{s,k,n}(t^{s,k,n}_i - 1)}^{H^{s,k,n}(t^{s,k,n}_i)} \int_{t^{s,k,n}_h}^{t^{s,k,n}_i} \theta^{s,k,n} \left( u | \tilde{\mathcal{F}}_u, \lambda_{\tilde{N}(u + 1)} \right) du. \quad (12)$$

11
Note that the intensity is integrated between $t_{s,k,n}^{i-1}$ and $t_{s,k,n}^i$ piecewise, where the pieces are determined either by an arrival time $t_i$, which includes the arrival times $t_{k,n}^{i-1}$, or by an arrival time $\tilde{t}_{s,k,n}^i$. The innovation term in equation (11) is defined in that way, since $\Theta_{s,k,n}^{i-1, t_{s,k,n}^i | \tilde{F} - t_{s,k,n}^i, \lambda_{\sim N}(t_{s,k,n}^i)} \sim \text{i.i.d. Exp}(1)$ and hence

$$\ln \Theta_{s,k,n}^{i-1, t_{s,k,n}^i | \tilde{F} - t_{s,k,n}^i, \lambda_{\sim N}(t_{s,k,n}^i)} \sim \text{i.i.d. standard extreme value type I distribution with mean } -0.5772.$$

The survivor function $\bar{F}_{s,k,n}^{i-1, t_{k,n}^i | \tilde{F} - t_{k,n}^i, \lambda_{\sim N}(t_{k,n}^i)}$ in equation (7) is given by

$$\bar{F}_{s,k,n}^{i-1, t_{k,n}^i | \tilde{F} - t_{k,n}^i, \lambda_{\sim N}(t_{k,n}^i)} = \exp \left( -\Theta_{s,k,n}^{i-1, t_{k,n}^i | \tilde{F} - t_{k,n}^i, \lambda_{\sim N}(t_{k,n}^i)} \right),$$

where the integrated intensity is obtained piecewise according to equation (12).

**Latent Factor**

We assume that the dynamics of the latent factor are defined on the time scale $t_i$. This means the latent factor changes whenever there is an action of an investor in some currency pair. Since each intensity $\theta_{s,k,n}$ and each integrated intensity $\Theta_{s,k,n}$ depend on the current value of the latent factor, we induce at every time $t$ a contemporaneous correlation between all intensities $\theta_{s,k,n}$ through the latent factor. The magnitude of this possibly investor, currency pair or state dependent correlation is determined by the parameters $\delta_{s,k,n}$. The latent factor can therefore be interpreted as an unobservable time effect which affects the decisions (open, close) of all investors at every time $t$ by influencing the intensities of the corresponding processes. We can justify the existence of such an unobservable time effect in our model in several ways: i) (News) effects of news announcements, not modelled due to data limitations, ii) (Order Flow) buy or sell pressure from the interbank market, which we do not observe directly since we consider an internet trading platform or iii) (Herding) similar behavior of traders, due to similar interpretations of any kind of technical chart patterns or further information.

In our model we assume that the latent factor follows, conditional on $\tilde{F}_{t_i}$, a lognormal distribution:

$$\ln \lambda_i | \tilde{F}_{t_i} \sim \text{i.i.d. N}(\mu_i, 1)$$

where the dynamics is modelled through an AR(1) process

$$\ln \lambda_i = a \ln \lambda_{i-1} + \epsilon_i \quad \text{for} \quad i = 1, \ldots, I,$$
with $\epsilon_i \overset{i.i.d.}{\sim} N(0, 1)$. Let $l_i$ denote the log of the latent factor at $t_i$:

$$l_i \equiv \ln \lambda_i,$$

and let $L_i$ denote the history of the log latent factor up to and including $t_i$:

$$L_i = \{l_j\}_{j=1}^i.$$

With this specification, the (log) latent factor depends only on its own past, so we denote its conditional distribution by $p(l_i|L_{i-1})$. From equation (9) it follows that the influence of the log latent factor on the $s$ type intensity is given by $\delta_{s,k,n} \ln \lambda_i$, which we can denote by $\lambda_{i,s,k,n}$. Then we have that

$$\lambda_{i,s,k,n} = a\lambda_{i-1,s,k,n} + \delta_{s,k,n}\epsilon_i \quad \text{for} \quad i = 1, \ldots, I.$$

Therefore the variance of $\epsilon_i$ is set to unity, so that the conditional variance of $\lambda_{i,s,k,n}$ is equal to $(\delta_{s,k,n})^2$, which eases the interpretation of the parameter.\footnote{Note that this does not exclude the possibility that $\delta_{s,k,n}$ could be negative.}

In the application we consider two model specifications – an unrestricted one, in which the intrinsic intensity dynamic structure is both driven by the ACI dynamics and the latent factor dynamics, and a restricted one, which only relies on the latent factor dynamics but not on the ACI part (i.e. $A^s = 0, B = 0$), to check whether the dynamics can solely explained by the latent factor. A detailed description of the estimation of the panel intensity model is presented in Appendix A.

\section{Empirical Analysis}

\subsection{Data Description}

We analyze an activity dataset of 2120 investors trading on the Internet trading platform OANDA FXTrade for the period from 00:00:00 on 1\textsuperscript{st} October 2003 until 23:59:59 on 31\textsuperscript{st} October 2003.\footnote{A detailed description of the dataset is contained in Lechner & Nolte (2007) and Nolte (2006).} The investors can trade in up to 30 currency pairs, including the most active ones such as EUR/USD, GBP/USD, USD/CHF, EUR/JPY, USD/JPY, etc. Trades can be initiated by market orders, limit orders, stop-loss or take-profit orders. Additionally, a trader can cancel an order, modify an existing limit order or change the stop-loss or take-profit limits. In our analysis we will only consider those actions which either lead to opening a new position, changing an existing position, changing an existing position,
or closing a position. Those are market orders, executed limit orders, or executed stop-loss and take-profit orders.

Since the traders on OANDA FXTrade are rather heterogeneous with respect to their trading activity and volume, we classify them into 20 groups, each corresponding to 5% of the cumulative distribution (vingintiles) of total trading volume (in USD) over the period. Thus, the first group (the 0% - 5% bin) contains the traders with the smallest trading volume, and the last group (the 95% - 100% bin) contains the traders with the largest total trading volume. We require that each trader has at least 30 transactions and has been active in at least three currency pairs during the month, resulting in 46 investors for each group. From each group we choose 5 investors randomly for which we estimate the model. Table 1 contains descriptive statistics for the traders in each group.

<table>
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<tr>
<th>Bin</th>
<th>0% - 5%</th>
<th>10%</th>
<th>15%</th>
<th>20%</th>
<th>25%</th>
<th>30%</th>
<th>35%</th>
<th>40%</th>
<th>45%</th>
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<tr>
<td>Real. P/L</td>
<td>0.67</td>
<td>3.13</td>
<td>-4.90</td>
<td>-26.67</td>
<td>-7.03</td>
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<td>-42.41</td>
<td>60.88</td>
<td>-90.94</td>
<td>96.33</td>
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<td>Med. Tr. Vol.</td>
<td>22.57</td>
<td>85.43</td>
<td>378.70</td>
<td>489.46</td>
<td>188.38</td>
<td>783.92</td>
<td>1179.06</td>
<td>2736.42</td>
<td>3636.93</td>
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<td>Max. Tr. Vol.</td>
<td>154.08</td>
<td>413.41</td>
<td>2215.71</td>
<td>1211.17</td>
<td>3403.07</td>
<td>1996.05</td>
<td>5846.61</td>
<td>11.4T</td>
<td>8263.19</td>
<td>13.9T</td>
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<tr>
<td>Tot. Tr. Vol.</td>
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<td>9784.29</td>
<td>23.7T</td>
<td>39.4T</td>
<td>63.0T</td>
<td>92.1T</td>
<td>137.3T</td>
<td>187.8T</td>
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<td>195.60</td>
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<td>43.00</td>
<td>52.00</td>
<td>3403.07</td>
<td>1996.05</td>
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<td>11.4T</td>
<td>8263.19</td>
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<td>218.80</td>
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<td>43.60</td>
<td>37.80</td>
<td>43.60</td>
<td>73.00</td>
<td>72.60</td>
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Table 1: Descriptive statistics for the 20 investor groups. All figures are averages over the 5 investors within each group. All currency values have been converted to USD. Real. P/L stands for realized profit/loss, Tr. – for transaction, Vol. – for volume, op. – for open, cl. – for close, M ≜ Million and T ≜ Thousand.

Although we observe that the magnitude of the realized profit or loss increases over the groups, there is no evidence that bigger investors are more profitable than smaller ones. There is no clear pattern in the frequency of trading among the investor groups, which lies between 57.6 and 672 trades per investor per month for groups 17 and 5, respectively.

As a further descriptive tool for analyzing deterministic intradaily trading patterns, we estimate a Nadaraya-Watson kernel regression separately for opening and closing
trades. To check if there are differences among traders located in different areas we separate the traders into three groups: American traders with accounting currency USD or CAD, European traders with accounting currency EUR, CHF or GBP and Asian traders with accounting currency JPY or AUD.

**Figure 2:** Seasonality patterns of trader activity. Traders are assigned to each group according to their accounting currency: USD and CAD – America, EUR, CHF and GBP – Europe, and JPY and AUD – Asia. The x-axis denotes time of day in Eastern Standard Time. Each function is estimated by Nadaraya-Watson kernel regression with 1440 nodes (24 hours × 60 minutes).

It is evident from the figure that the diurnal seasonality pattern is similar across traders and transaction types (open or close). One general pattern emerges among all traders: a pronounced peak in activity from 8:30 to 10:00 EST and a minor peak at around 3:00 – 4:00 EST, which corresponds to 8:00 – 9:00 GMT. The peak at 23:00 EST for the traders with JPY or AUD as an accounting currency coincides with the after-lunch period in Tokyo (13:00). This pronounced similarity in the seasonality among all traders led us to use a common seasonality component in the intensity specification.
In addition to the activity data set from OANDA FXTrade we include in our analysis the bid-ask spreads for each of the 30 currency pairs from the interbank market provided by Olsen Financial Technologies.

3.2 Estimation Results

In this section we report the estimation results of the panel intensity model and evaluate its performance. A detailed discussion of the implications of the results in light of behavioral finance and market microstructure theory is relegated to section 4.

We estimate the model separately for each of the 20 investor groups and consider two model specifications – the fully specified version and the restricted version without ACI dynamics as described in Section 2.2.

The estimation results for the fully specified model for all 20 investor groups are collected in Appendix B in Tables 5 to 8. We have grouped the estimates into several categories: baseline intensity, latent factor, seasonality, dynamics and covariates. The covariates correspond to observable variables in the traders’ information sets, which can vary during the inter-event durations. In our specification we include the percentage bid-ask spread on the interbank market ($\gamma \cdot \text{spread}$), the current paper profit/loss in the currency pair ($\gamma \cdot \text{P/L}_1$), the paper profit/loss in the portfolio of all positions ($\gamma \cdot \text{P/L}_{\text{pf}}$) and volume ($\gamma \cdot \text{vol}$) into both the opening and closing intensity sub-processes. The paper profit/loss is computed as the potential profit or loss (denominated in USD) that would have been obtained, if the trader had decided to close his position at the prevailing market rates at each point of time. The portfolio paper profit/loss is the sum over the paper profit/losses of all open positions. The volume variable is computed as the standardized excess cumulative transaction volume and measures the relative exposure of the trader. Values larger than zero indicate that the trader has currently a higher-than-normal exposure. The first three covariates vary over the inter-event durations, while the volume variable does not and is only updated at the open and close event times.

Altogether, the coefficients for the baseline intensity for all groups and all investors result in a monotonically decreasing intensity, which implies that, ceteris paribus, the longer the periods of no activity, the lower the instantaneous probability for an open or close trade. The location parameters $\omega_n$ determine the individual intercept from which on the baseline intensity is monotonically decreasing. Across groups and investors, we do not observe any systematic relationships in the sense that the baseline open intensity is higher than the baseline close intensity or vice versa.

Although the shape of the seasonality pattern differs slightly across investor groups it
generally corresponds to the one resulting from the Nadaraya-Watson kernel regression and we refrain from plotting it again. The weekend dummy is significantly negative for all groups which is in line with the lower trading activity during the weekends. The parameters for the impact of the latent factor $a$, $\delta^o$, and $\delta^c$ are jointly highly significant for all 20 investor groups. Whereas the impact parameters $\delta^o$ are always greater and $\delta^c$ are always smaller than than zero, the autoregressive parameter $a$ shows no systematic pattern regarding its sign. In absolute value $a$ is always smaller than one, which ensures a stationary AR(1) process for the latent factors. For groups with negative $a$ the latent factor might capture effects induced by alternating open and close trades, whereas for groups with positive $a$ the latent factor might instead capture a kind of habit persistence or momentum in the open and close trading pattern. This interpretation has limited significance, since the latent factor evolves over the pooled process of all investor and currency specific open and close sub-processes, so that no clear implication for the trading dynamics of the individual and even for the groups of investors can be derived. It should be noted, however, that for $a > 0$ indicates a clustering of open and close transactions, while $a < 0$ captures an alternating open-close pattern.

The autoregressive parameters $A^s$ and $B$ in the ACI specification vary considerably across investor groups and additionally capture differences in trading patterns. In order to check whether the specification of the dynamic structure contributes significantly to the model fit, we conduct likelihood ratio tests, reported in Table 2. With the exception of group 14, all tests strongly suggest that the ACI part of the model is necessary for capturing the dynamics of the trading process and that we should not rely solely on the latent factor induced dynamics.

The goodness-of-fit of the models is evaluated by comparing properties of the “raw” inter-event durations, to the model residuals. In an intensity-based framework, the integrated intensities (see equation (12)) can be considered as generalized residuals.

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Table 2: Test statistics and p-values for the likelihood ratio test for the full model specification against the restricted model specification without ACI dynamics. The test statistic is asymptotically $\chi^2_6$-distributed.

The goodness-of-fit of the models is evaluated by comparing properties of the “raw” inter-event durations, to the model residuals. In an intensity-based framework, the integrated intensities (see equation (12)) can be considered as generalized residuals.
which under the correct model specification should be i.i.d exponentially distributed with mean 1. The goodness-of-fit diagnostics, are given in Tables 3 and 4. While we still detect a slight over-dispersion of the residuals, which indicates some degree of misspecification, also evident in the QQ-plots in Figures 3 and 4, the dynamic properties of the inter-event durations are captured quite reasonably by the model. This is confirmed by the Ljung-Box test and the Brock, Dechert & Scheinkman (1987) (BDS) test. We observe that the Ljung-Box statistics of the generalized residual series decrease considerably in comparison to those of the raw data series in the majority of cases. The same observation also holds for the BDS test statistics, which not merely tests for uncorrelatedness but for i.i.d.ness. Possibilities for improving the model fit are to consider alternative baseline intensity functions, richer ACI specifications and additional latent factors with the aim for allowing for a broader set of individual and currency-specific effects.
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Table 3: Diagnostics for the raw and the residual series of the open and close sub-processes for investor groups 1 to 10. The series are pooled over currency pairs and investors. LB $\triangleq$ Ljung-Box test statistic, BDS(m=embedding dimension) $\triangleq$ Brock-Dechert-Scheinkman test statistic $\sim N(0, 1)$. 
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Table 4: Diagnostics for the raw and the residual series of the open and close sub-processes for investor groups 11 to 20. The series are pooled over currency pairs and investors. LB \( \triangleq \) Ljung-Box test statistic, BDS(m=embedding dimension) \( \triangleq \) Brock-Dechert-Scheinkman test statistic \( \sim N(0,1) \).
Figure 3: Quantile-Quantile plots of open sub-process residual series against the unit exponential distribution. The plots correspond from the upper left panel to the lower right one to investor groups 1 to 20.
Figure 4: Quantile-Quantile plots of close sub-process residual series against the unit exponential distribution. The plots correspond from the upper left panel to the lower right one to investor groups 1 to 20.
4 Behavioral Finance and Market Microstructure Implications

In this section we discuss the estimation results stated in Appendix B in Tables 5 to 8 for all 20 investor groups in light of market microstructure and behavioral finance theories. Overall, the obtained results related to the interpretation of the explanatory variables – spread, single position profit/loss, portfolio profit/loss and volume – are very robust to the choice of full or restricted model specification which underpins the validity of the derived effects.

The proposed panel intensity model allows us to view the disposition effect and investors’ overconfidence from a broader perspective than in the literature cited in the Introduction by focusing on the individual trader micro-level and considering the timing of trading decisions as central to the analysis. After all, the disposition effect is explicitly defined as a time effect, for the analysis of which our framework is perfectly suited. Main advantages of the model are its ability to include observable individual heterogeneity through individual fixed effects and time-varying covariates describing the investors’ information set as well as to account for unobservable time-varying effects through the latent factor. In our framework, investor overconfidence is modelled alongside the disposition effect while controlling for market liquidity, which allows us to disentangle the impacts of these behavioral biases on individual trading patterns. Furthermore, we analyze to which degree the portfolio profit/loss affects trading decisions in the separate currency pairs and amplifies or dampens the security-specific disposition effects. The partitioning of the population of investors into groups enables us to analyze the differences in the degree to which certain groups are prone to behavioral biases.

We follow the literature and measure overconfidence by standardized excess cumulative trading volume. Although excess volume might not be the perfect measure of overconfidence, we consider it to be a rather good proxy, which is motivated by the overwhelming theoretical and empirical evidence cited above. Thus, we interpret trading volume in excess of the standardized average as a sign of investor overconfidence. We include the percentage bid-ask spread as a control variable to capture the impact of market liquidity or uncertainty, which might otherwise be solely reflected in the trading volume. The disposition effect is directly analyzed by means of the paper profit/loss in the single position.

In Figure 5 we plot the parameters for the percentage bid-ask spread, the single position paper profit/loss, the portfolio paper profit/loss and the standardized excess
cumulative trading volume for the both open and close intensity sub-processes and across the 20 investor groups, ordered on the x-axis. The solid dots represent the estimated coefficients (with the corresponding 95% confidence intervals). The solid line is the OLS regression fit through the estimated coefficients.
Figure 5: Parameter estimates for the single position paper profit/loss, the portfolio paper profit/loss, the standardized excess cumulative transaction volume and the percentage bid-ask spread for both open and close intensity sub-processes across the 20 investor groups, ordered on the x-axis. The solid dot represents the estimated coefficient and the bars represent the 95% confidence bounds. The solid line is the OLS regression fit through the estimated coefficients.
We first focus on the upper-row panel illustrating the impact of the paper profit/loss in the single position ($\gamma_{P/L}$) on the open and close intensities. In general, we observe that the coefficients on the opening intensity are negative, while those for the closing intensity are positive. Moreover, while there is no trend for the open sub-process, the impact of the variable on the closing intensity is decreasing, the larger the investors in the group. A positive sign of the coefficient for the closing intensity implies that the higher the profit (loss), the higher (lower) the intensity to close the position. Thus, we find strong evidence for the presence of a disposition effect for small investors which diminishes as investors become larger. This is in line with the findings of Shapira & Venezia (2001), Dhar & Zhu (2006), Goetzmann & Massa (2004) and Chen et al. (2007) stated above. The coefficient for the open intensity cannot be interpreted in light of the narrow definition of the disposition effect, which only considers the relative propensity to realize profits compared to losses, restricting the analysis to closing events. The prospect theory of Kahneman & Tversky (1979) is a more general concept, which describes an investor as being risk averse when winning, and risk seeking when losing. This implies that an investor would be less willing to increase his exposure as his position becomes more profitable. The negative coefficients for the open intensity are perfectly consistent with such behavior, and hence allow for a more general interpretation of the disposition effect.

The second-row panel depicts the influence of the paper profit/loss in the portfolio of positions ($\gamma_{P/L, pf}$) on both intensities. This variable can be considered as a complementary decision factor, which sheds new light on traders’ behavior and the disposition effect. While the impact on the open intensity is ambiguous and often insignificant, the larger investors are significantly influenced by the success of their total portfolio in their decision to close positions. We find that these investors tend to close each of their positions faster when their portfolio is generating profits which indicates that these more sophisticated investors employ a broader portfolio investment strategy. Contrary to this, smaller investors seem to be narrow framed and oblivious to the dependencies between their positions in the portfolio. This effect cannot be attributed to smaller investors holding only a single position, as the groups have been selected so that all traders are invested in at least three currency pairs. From a different perspective, these findings can be interpreted as a higher level of disposition effect to which larger investors are more susceptible.

The plots in the third-row panel present strong evidence in support of the presence of overconfident behavior. We observe very clearly that standardized excess trading volume ($\gamma_{vol}$) has a positive influence on the further open intensity and a negative
impact on the closing intensity. This pattern is very robust over all 20 investor groups and perfectly in line with the presumption that overconfidence generates more trading activity. The results imply that overconfidence not only leads to more trading, but also to longer holding periods, since the open intensity increases while the closing intensity decreases, thus implying a systematic increase in the exposure to currency risk. We consider this an interesting finding, which can only be verified in a model framework, in which time plays a central role. Such risk-taking behavior can be interpreted as a facet of the concept of illusion of self-control (c.f. Langer (1975), Barber & Odean (2001b)) or as existence of an anchoring effect (c.f. Slovic & Lichtenstein (1971), Kahneman (1992)).

From a more general perspective, we observe that overconfidence implies clusters of high risk exposures on the individual trader level. This opens avenues for further research on the relationship between trading behavior on the micro-level and market-wide phenomena, such as volatility clustering, pervasive in all financial markets.

Concerning the last-row panel of the figure, the spread coefficients \((\gamma_{spread})\) are largely insignificant, and the only conclusion we draw is that the largest four investor groups exhibit a negative predisposition to close positions when spreads are wide.

Overall our results are consistent with the theoretical and empirical findings for the disposition effect and overconfidence as well as the discrimination of these effects across different groups of investors. The novelty of the proposed modeling framework is that it highlights the importance of the time dimension, the separate open and close intensity processes, individual heterogeneity and allows for a joint analysis of complex individual trading strategies in light of behavioral finance theories. The proposed approach delivers new insights into the study of behavioral biases, by allowing us to adopt a more general interpretation of the prospect theory. The inclusion of the portfolio profit/loss opens new avenues for the investigation and interpretation of the disposition effect and the analysis of trading patterns.
5 Conclusion

In this paper we propose an econometric model for the analysis of complex trading activity datasets within an intensity based framework. Such datasets contain very detailed information about the trading history of single traders, and provide more insights into the market microstructure and investors’ trading behavior beyond the informational content of typical high-frequency datasets. From an econometric point of view, analyzing activity datasets is rather challenging, due to their multidimensional panel structure spanning time, types of trading activity, securities and investors, and irregularly spaced observations. The model developed in the paper, is suited to cope with this data structure.

An attractive feature of the intensity-based framework is its flexibility in terms of capturing the impact of observable time-varying covariates on the underlying processes. Since not all information can be observed, however, we include a latent factor in the model which is responsible for capturing hidden correlation structures. We estimate the panel intensity model adopting the efficient importance sampling algorithm of Richard & Zhang (2007).

The model is applied to a trading activity dataset from OANDA FXTrade in order to analyze the trading behavior of different groups of investors, categorized according to their investment turnover. The beauty of the methodology is that time plays the central role, which allows us to draw immediate conclusions with respect to behavioral biases influencing the timing of investment decisions, such as the disposition effect.

We find that the standard disposition effect is complemented by the impact of the total portfolio performance on the length of investment periods. The joint modelling of the processes leading to opening and closing financial positions allows for a broader interpretation of the disposition effect in light of the prospect theory of Kahneman & Tversky (1979). Apart from new insights into the disposition effect, the model delivers detailed insights into investors’ overconfidence, which we find to lead to clustering of trades and to longer holding periods.

The obtained results are very robust to the model parametrization and the quality of the fit is reasonable. The suggested model, however, can be extended in several directions: inclusion of individual and/or currency specific effects in further components of the intensity specification, a richer ACI dynamics specification, more flexible baseline intensity parameterizations and additional and/or different dynamics for the latent factor process. Furthermore, the model can be extended to account for the different order types used to open or close positions.
References


A Appendix: Estimation

We consider the explicit form and the estimation of the parameters in the likelihood function. Let \( W \) denote the set of data matrices \( W^{k,n} \) for each currency pair \( k = 1, \ldots, K \) and investor \( n = 1, \ldots, N \) where the \( i^{th} \) row of \( W^{k,n}, w_i^{k,n} \), consists of the following data:

\[
w_i^{k,n} = (t_i^{k,n}, d_i^{1,k,n}, \ldots, d_i^{S,k,n}), \quad \text{with } i = 1, \ldots, I^{k,n}.
\]

With \( W_i^{k,n} \) we denote the history of \( w_i^{k,n} \) up to and including \( t_i^{k,n} \), i.e.:

\[
W_i^{k,n} = \{w_j^{k,n}\}_{j=1}^i.
\]

Furthermore, let \( \hat{Z}_i^{k,n} \) for \( k = 1, \ldots, K \) and \( n = 1, \ldots, N \) denote the set consisting of the following time-varying covariate data:

\[
\hat{Z}_i^{k,n} = \{\{z_j^{1,k,n} | j = 1, \ldots, M_i^{1,k,n}(t_i^{k,n})\}, \ldots, \{z_j^{S,k,n} | j = 1, \ldots, M_i^{S,k,n}(t_i^{k,n})\}\}.
\]

Recall that the likelihood function of our model is given by

\[
L(W; \theta) = \int_{\mathbb{R}^t} \prod_{n=1}^N \prod_{k=1}^K \prod_{i=1}^{I^{k,n}} \prod_{s=1}^S \mathbb{F}(s,k,n) \left( t_i^{k,n}, t_i^{k,n} \mid \hat{S}_i^{k,n}, \hat{\Lambda}(t_i^{k,n}+1) \right) \left( \theta_{s,k,n} \left( t_i^{k,n} \mid \hat{S}_i^{k,n}, \hat{\Lambda}(t_i^{k,n}+1) \right) \right) d\theta_{s,k,n} \rho(\hat{\Lambda}(t_i^{k,n}+1) \mid \hat{S}_i^{k,n}) d\Lambda
\]

\[
= \int_{\mathbb{R}^t} \prod_{n=1}^N \prod_{k=1}^K \prod_{i=1}^{I^{k,n}} \prod_{s=1}^S \mathbb{F}(s,k,n) \left( t_i^{k,n}, t_i^{k,n} \mid \hat{S}_i^{k,n}, \exp(l_N(t_i^{k,n})) \right) \left( \theta_{s,k,n} \left( t_i^{k,n} \mid \hat{S}_i^{k,n}, \exp(l_N(t_i^{k,n})) \right) \right) d\theta_{s,k,n} \rho(l_N(t_i^{k,n}) \mid L_N(t_i^{k,n})-1) dL
\]

\[
= \int_{\mathbb{R}^t} \prod_{i=1}^I \prod_{c_i} \prod_{s=1}^S \mathbb{F}(s,k,n) \left( t_i^{k,n}, t_i^{k,n} \mid \hat{S}_i^{k,n}, \exp\left( -\frac{(l_i - \mu_i)^2}{2} \right) \right) \frac{1}{\sqrt{2\pi}} d\theta_{s,k,n}
\]

where \( L = \ln \Lambda \) and the second equality follows from a change of the variable \( \lambda \) to \( l \).

Using the datasets defined above, the likelihood function can be rewritten as

\[
L(W; \theta) = \int_{\mathbb{R}^t} \prod_{i=1}^I \prod_{c_i} g_{N^{k,n}(t_i)} \left( t_i^{k,n}, \hat{Z}_i^{k,n}(t_i) \right) p(l_i \mid L_i-1) dL
\]

\[
= \int_{\mathbb{R}^t} \prod_{i=1}^I \prod_{c_i} \varphi_{N^{k,n}(t_i)} \left( t_i^{k,n}, l_i \mid \hat{Z}_i^{k,n}(t_i) \right) dL, \quad (13)
\]
where \( g^{k,n} \) denotes the product of the survivor and the intensity functions, \( p \) the density of the conditional normal distribution and \( \varphi^{k,n} \) the resulting corresponding joint conditional density. Since this likelihood involves the computation of an \( I \)-dimensional integral, we employ the Efficient Importance Sampling (EIS) technique of Lissenfeld & Richard (2003), which has been used for estimating stochastic conditional intensity models by Bauwens & Hautsch (2006). The EIS technique is based on simulation of the likelihood function (13) which can be rewritten as

\[
\mathcal{L}(W; \theta) = \int_{\mathbb{R}^+} \prod_{i=1}^I \varphi^{k,n} \left( w^{k,n}_{Nk,n(t_i)}, l_i|W_{Nk,n(t_i)-1}, L_{i-1}, \tilde{Z}^{k,n}_{Nk,n(t_i)} \right) \frac{m(l_i|L_{i-1}, \phi_i)}{\prod_{i=1}^I \prod_{i} m(l_i|L_{i-1}, \phi_i)} dL,
\]

where \( m(l_i|L_{i-1}, \phi_i) \) is a sequence of auxiliary importance samplers which are used to draw a trajectory of the latent factor, given some additional parameters \( \phi_i \) of the sampler. The estimation then proceeds by generating \( R \) trajectories of the latent factor and averaging over the draws

\[
\mathcal{L}_R(W; \theta) = \frac{1}{R} \sum_{r=1}^R \prod_{i=1}^I \prod_{i} \varphi^{k,n} \left( w^{k,n}_{Nk,n(t_i)}, l_i^{(r)}|W_{Nk,n(t_i)-1}, L_{i-1}^{(r)}, \tilde{Z}^{k,n}_{Nk,n(t_i)} \right) \frac{m(l_i^{(r)}|L_{i-1}^{(r)}, \phi_i)}{\prod_{i=1}^I \prod_{i} m(l_i^{(r)}|L_{i-1}^{(r)}, \phi_i)},
\]

(14)

where the bracketed superscript \( r \) indicates the values of the corresponding variable or set for the \( r \)-th repetition. The idea of the EIS approach is to find the values of the parameters \( \phi_i \) for \( i = 1, \ldots, I \) such that the sampling variance of \( \mathcal{L}_R(W; \theta) \) is minimized. For ease of illustration denote the numerator in equation (14) by \( \varphi(W, L^{(r)}|\theta) = g(W|L^{(r)}, \theta)p(L^{(r)}) \), where the generic parameter vector \( \theta \) appears now, and the denominator by \( m(L^{(r)}|\phi) \). A more elaborate presentation can be found in Richard & Zhang (2007). The sampling variance of \( \mathcal{L}_R(W; \theta) \) is given by

\[
V(\mathcal{L}_R(W; \theta)) = \frac{\mathcal{L}(W; \theta)}{R} \frac{1}{\mathcal{L}(W; \theta)} \mathcal{V} \left( \varphi(W, L^{(r)}|\theta) \right) = \frac{\mathcal{L}(W; \theta)}{R} \frac{1}{\mathcal{L}(W; \theta)} \int_{\mathbb{R}^+} \left( \frac{\varphi(W, L|\theta)}{m(L|\phi)} - \mathcal{L}(W; \theta) \right) m(L|\phi) dL \ (15)
\]

If we are able to choose \( \phi \) such that \( m(L|\phi) = \varphi(W, L|\theta) \) the sampling variance would be zero. Since this case is very unrealistic the aim is to find \( \phi \) such that \( m(L|\phi) \) is very close to \( \varphi(W, L|\theta) \) under the restriction that \( m(L|\phi) \) is analytically integrable.
Furthermore $m(L|\phi)$ can be decomposed into

$$m(L|\phi) = \frac{k(L, \phi)}{\chi(\phi)}$$ (16)

where $k(L, \phi)$ and $\chi(\phi) = \int_{\mathbb{R}^+} k(L, \phi)dL$ can either be interpreted as joint and marginal density or as kernel and integration constant. Defining $d(L; \varphi, \theta)$ as

$$d(L; \varphi, \theta) = \ln \left( \frac{\varphi(W, L|\theta)}{\mathcal{L}(W; \theta)m(L|\phi)} \right)$$ (17)

and defining $h(x)$ as

$$h(x) = \exp(\sqrt{x}) + \exp(-\sqrt{x}) - 2$$ (20)

allows to rewrite equation (15) as

$$V(\mathcal{L}_R(W; \theta)) = \mathcal{L}(W; \theta) R \int_{\mathbb{R}^+} h((d(L; \phi, \theta)^2) \varphi(W, L|\theta)dL.$$ (21)

This equation defines a nonlinear Generalized Least Squares problem in $\phi$, since $h$ is monotone and convex on $\mathbb{R}^+$. The power series representation of $h$ is given by

$$h(x) = \sum_{i=1}^{\infty} \frac{x^i}{(2i)!}$$ (22)

Using the series expansion of order one for $h$, which is $h(x) = x$ equation (21) simplifies to

$$V(\mathcal{L}_R(W; \theta)) = \frac{\mathcal{L}(W; \theta)}{R} \int_{\mathbb{R}^+} d(L; \phi, \theta)^2 \varphi(W, L|\theta)dL,$$ (23)

and the minimization problem becomes

$$\hat{\phi}(\theta) = \arg\min_{\phi} \int_{\mathbb{R}^+} d(L; \phi, \theta)^2 \varphi(W, L|\theta)dL$$

$$= \arg\min_{\phi} \int_{\mathbb{R}^+} d(L; \phi, \theta)^2 g(W|L, \theta)p(L)dL$$ (24)

The integral in equation (24) is computed by its Monte Carlo proxy given by

$$\frac{1}{R} \sum_{r=1}^{R} d(L^{(r)}; \phi, \theta)^2 g(W|L^{(r)}, \theta)$$
where $L^{(r)}$ denote trajectories of length $I$ sampled from the initial sampler $p$ and $\hat{\phi}(\theta)$ is determined based on this approximation. Since the $L^{(r)}$ generate a high variance of $g$ Richard & Zhang (2007) propose to drop the weight function $g$ from the equation and compute $\hat{\phi}(\theta)$ on the basis of the unweighted problem. Therefore the minimization problem is given by

$$\hat{\phi}(\theta) = \text{argmin}_\phi \sum_{r=1}^{R} d(L^{(r)}; \phi, \theta)^2. \quad (25)$$

Writing $d(L^{(r)}; \phi, \theta)$ explicitly yields

$$d(L^{(r)}; \phi, \theta) = \ln \left( \frac{\prod_{i=1}^{I} \prod_{C_i} \varphi^{k,n}(w_{N,k,n}^{(k,k-n)}(t_i), t_i^{(r)}|W_{N,k,n}^{(k,k-n)}(t_i-1), L_{i-1}^{(r)}, \tilde{Z}_{N,k,n}^{k,n}(t_i))}{\prod_{i=1}^{I} \prod_{C_i} m(l_i^{(r)}|L_{i-1}^{(r)}, \phi_i)} \right) - \ln (\mathcal{L}(W; \theta)). \quad (26)$$

Substituting

$$m(l_i^{(r)}|L_{i-1}^{(r)}, \phi_i) = \frac{k(L_i^{(r)}, \phi_i)}{\chi(\phi_i, L_{i-1}^{(r)})} \quad (27)$$

yields

$$d(L^{(r)}; \phi, \theta) = \ln \left( \prod_{i=1}^{I} \prod_{C_i} \varphi^{k,n}(w_{N,k,n}^{(k,k-n)}(t_i), t_i^{(r)}|W_{N,k,n}^{(k,k-n)}(t_i-1), L_{i-1}^{(r)}, \tilde{Z}_{N,k,n}^{k,n}(t_i)) \chi(\phi_i, L_{i-1}^{(r)}) \right)$$

$$- \ln \left( \prod_{i=1}^{I} \prod_{C_i} k(L_i^{(r)}, \phi_i) \right) - \ln (\mathcal{L}(W; \theta))$$

$$= \ln \left( \prod_{i=1}^{I} \prod_{C_i} \varphi^{k,n}(w_{N,k,n}^{(k,k-n)}(t_i), t_i^{(r)}|W_{N,k,n}^{(k,k-n)}(t_i-1), L_{i-1}^{(r)}, \tilde{Z}_{N,k,n}^{k,n}(t_i)) \chi(\phi_{i+1}, L_i^{(r)}) \right)$$

$$- \ln \left( \prod_{i=1}^{I} \prod_{C_i} k(L_i^{(r)}, \phi_i) \right) - \ln (\mathcal{L}(W; \theta)) + \ln (\chi(\phi_1, L_0^{(r)}))$$

where $\chi(\phi_{i+1}, L_i^{(r)}) \equiv 1$. The thereto related minimization problem (25) can now be solved sequentially using a backward recursion from $I \to 1$ which yields $\phi = \{\phi_i|i = I, \ldots, 1\}$. The sequential problem consists then at each $i = 1, \ldots, I$ of approximating

$$\ln \left( \prod_{C_i} \varphi^{k,n}(w_{N,k,n}^{(k,k-n)}(t_i), t_i^{(r)}|W_{N,k,n}^{(k,k-n)}(t_i-1), L_{i-1}^{(r)}, \tilde{Z}_{N,k,n}^{k,n}(t_i)) \chi(\phi_{i+1}, L_i^{(r)}) \right)$$
Thus $\hat{\phi}_i(\theta)$ is obtained through

$$
\hat{\phi}_i(\theta) = \arg\min_{\phi_i} \sum_{r=1}^{R} \left( \ln \left( \prod_{c_i} g^{k,n}(w_{Nk,n(t_i)}^{k,n} | W_{Nk,n(t_i)-1}^{k,n}, \tilde{Z}_{Nk,n(t_i)}^{k,n} ) \chi \left( \phi_{i+1}, L_i^{(r)} \right) \right) \\
- \phi_{0,i} - \ln \left( k \left( L_i^{(r)}, \phi_i \right) \right) \right)^2.
$$

(28)

The additional coefficients $\phi_{0,i}$ are scalars which capture corresponding components of $\ln (\mathcal{L}(W; \theta))$, which are still unobservable. As Liesenfeld & Richard (2003) note, a sensible choice for the class of kernels for the auxiliary samplers $m$ is a parametric extension to the direct samplers $p$ given by

$$
k(L_i, \phi_i) = p(l_i | L_{i-1}) \zeta \left( l_i, \phi_i \right),
$$

where $\zeta$ is itself a Gaussian density kernel given by

$$
\zeta \left( l_i, \phi_i \right) = \exp \left( \phi_1 l_i + \phi_2 l_i^2 \right).
$$

Since a product of normal kernels is a normal kernel as well, we obtain for $k(L_i, \phi_i)$

$$
k(L_i, \phi_i) \propto \exp \left( (\phi_1, i + \mu_i) l_i + \left( \phi_2, i - \frac{1}{2} \right) l_i^2 - \frac{1}{2} \mu_i^2 \right)
$$

$$
= \exp \left( -\frac{1}{2\pi_i^2} (l_i - \kappa_i)^2 \right) \exp \left( \frac{\kappa_i^2}{2\pi_i^2} - \frac{1}{2} \mu_i^2 \right),
$$

where

$$
\pi_i^2 = (1 - 2\phi_2, i)^{-1}, \quad \text{and} \quad \kappa_i = (\phi_1, i + \mu_i) \pi_i^2.
$$

(29)

(30)

It follows that

$$
\chi(\phi_i, L_{i-1}) = \exp \left( \frac{\kappa_i^2}{2\pi_i^2} - \frac{\mu_i^2}{2} \right).
$$

(31)

Under this choice of kernels class, $p(l_i | L_{i-1})$ cancels out in the minimization problem (28), which can then be rewritten as

$$
\hat{\phi}_i(\theta) = \arg\min_{\phi_i} \sum_{r=1}^{R} \left( \ln \left( \prod_{c_i} g^{k,n}(w_{Nk,n(t_i)}^{k,n} | W_{Nk,n(t_i)-1}^{k,n}, L_i^{(r)} , \tilde{Z}_{Nk,n(t_i)}^{k,n} ) \chi \left( \phi_{i+1}, L_i^{(r)} \right) \right) \\
- \phi_{0,i} - \ln \left( \zeta \left( l_i^{(r)}, \phi_i \right) \right) \right)^2.
$$

(32)
The implementation of the sequential ML-EIS approach can be summarized in the following steps:

**STEP 1.** Draw $R$ trajectories $\{l_i^{(r)}\}_{i=1}^I$ from $\{N(\mu_i, 1)\}_{i=1}^I$.

**STEP 2.** For each $i$ with $i : I \rightarrow 1$ solve the $R$-dimensional OLS problem in (32).

**STEP 3.** Calculate the sequences $\{\pi_i^2\}_{i=1}^I$ and $\{\kappa_i\}_{i=1}^I$ from equations (29) and (30) and draw $R$ trajectories of $\{l_i^{(r)}\}_{i=1}^I$ from $\{N(\kappa_i, \pi_i^2)\}_{i=1}^I$ to compute the likelihood function given in (14).
## B Appendix: Estimation Outputs

<table>
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<th>Par.</th>
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<th>Est. 2</th>
<th>Std.</th>
<th>Est. 3</th>
<th>Std.</th>
<th>Est. 4</th>
<th>Std.</th>
<th>Est. 5</th>
<th>Std.</th>
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### Table 5: Estimation results for investor groups 1 to 5. The \( \gamma \) coefficients on the covariates should be interpreted as follows: superscript “o” for opening intensity, superscript “c” for closing intensity.

The subscripts stand for the corresponding variable, where “spread” is the bid-ask spread in the interbank market, “P/L 1” is the paper profit/loss in the corresponding currency pair, “P/L pf” is the paper profit/loss in the total portfolio and “vol” is the standardized excess trading volume.

All other coefficients are detailed in the main text. Quasi-maximum likelihood standard errors reported.
Table 6: Estimation results for investor groups 6 to 10. The γ superscripts on the covariates should be interpreted as follows: superscript “o” for opening intensity; superscript “c” for closing intensity. The subscripts stand for the corresponding variable, where “spread” is the bid-ask spread in the interbank market, “P/L 1” is the paper profit/loss in the corresponding currency pair, “P/L pf” is the paper profit/loss in the total portfolio and “vol” is the standardized excess trading volume.

All other coefficients are detailed in the main text. Quasi-maximum likelihood standard errors are reported.
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Table 7: Estimation results for investor groups 11 to 15. The $\gamma$ coefficients on the covariates should be interpreted as follows: superscript “o” for opening intensity, superscript “c” for closing intensity. The subscripts stand for the corresponding variable, where “spread” is the bid-ask spread in the interbank market, “P/L 1” is the paper profit/loss in the corresponding currency pair, “P/L pf” is the paper profit/loss in the total portfolio and “vol” is the standardized excess trading volume. All other coefficients are detailed in the main text. Quasi-maximum likelihood standard errors reported.
Table 8: Estimation results for investor groups 16 to 20. The γ coefficients on the covariates should be interpreted as follows: superscript "o" for opening intensity, superscript "c" for closing intensity. The subscripts stand for the corresponding variable, where "spread" is the bid-ask spread in the interbank market, "P/L 1" is the paper profit/loss in the corresponding currency pair, "P/L pf" is the paper profit/loss in the total portfolio and "vol" is the standardized excess trading volume. All other coefficients are detailed in the main text. Quasi-maximum likelihood standard errors reported.