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DEPARTMENT OF ACCOUNTING AND FINANCE

ESSAYS ON RETAIL INVESTORS TRADING BEHAVIOR IN FX MARKETS

DOCTOR OF PHILOSOPHY DISSERTATION

THEOFILIA KAOURMA

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DEPARTMENT OF ACCOUNTING AND FINANCE

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THEOFILIA KAOURMA

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Theofilia Kaourma

Περίληψη

Η παρούσα διδακτορική διατριβή αφορά την διερεύνηση της συμπεριφοράς των ανεξάρτητων επενδυτών (individual investors) στην αγορά ξένου συναλλάγματος. Συγκεκριμένα σε μια σειρά εκθέσεων εξετάζεται πρώτον, το πως το γενικό συναίσθημα που λαμβάνεται από τα νέα και οι μακροοικονομικές ανακοινώσεις επηρεάζουν την δραστηριότητα και την συμπεριφορά των ανεξάρτητων επενδυτών, δεύτερον, πως διαμορφώνεται και πώς κατανέμεται η ανάληψη κινδύνων μεταξύ των ανεξάρτητων επενδυτών και τρίτον, αξιοποιώντας μια ξαφνική, εξαιρετικά βραχυπρόθεσμη, πτώση στην τιμή της στερλίνας (sterling flash crash incident), η οποία αποτελεί μια δραματική εξωγενή επενδυτική εμπειρία, εξετάζονται πιθανές επιδράσεις στην δραστηριότητα και την συμπεριφορά των ανεξάρτητων επενδυτών.

Το πρώτο κεφάλαιο ερευνά τη δραστηριότητα και τη συμπεριφορά των ανεξάρτητων επενδυτών στο πλαίσιο των μακροοικονομικών ανακοινώσεων καθώς και την επίδραση του δείκτη ψυχολογίας επενδυτών «investor sentiment index» σε αυτές. Η μελέτη χρησιμοποιεί ένα αποκλειστικό και ιδιόκτητο σύνολο δεδομένων παρέχοντας αξιόλογα συμπεράσματα για την συμπεριφοριακή δραστηριότητα τους. Συγκεκριμένα, η βάση δεδομένων περιλαμβάνει για κάθε λεπτό, τον ολικό όγκο συναλλαγών των ανεξάρτητων επενδυτών που αφορά την αγορά ή την πώληση του συναλλάγματος, ευρώ προς δολάριο. Δημιουργώντας και αναλύοντας την πεντάλεπτη φορά της ροής των θέσεων (5-minute order flow) των επενδυτών, τα αποτελέσματα υποδεικνύουν τη προβλεπτική ικανότητα του δείκτη ψυχολογίας επενδυτών πάνω στην φορά της επενδυτικής τους δραστηριότητας καθώς και την αντίστροφη επενδυτική τους συμπεριφορά σε σχέση με το περιεχόμενο των μακροοικονομικών ανακοινώσεων και της κίνησης των τιμών συναλλάγματος.

Το δεύτερο κεφάλαιο επικεντρώνεται στην διερεύνηση της ανάληψης κινδύνου από μέρους των ανεξάρτητων επενδυτών. Ο ορισμός αυτός εξετάστηκε με την χρήση της «μόχλευσης», ένα γνώρισμα που είναι χαρακτηριστικό στην αγορά ξένου συναλλάγματος και παρέχει μια άμεση μορφή μέτρησης του επιπέδου του κινδύνου που είναι διαθέσιμος ο επενδυτής να αναλάβει. Με την χρήση διάφορων χαρακτηριστικών του επενδυτή, όπως για παράδειγμα το φύλλο, την ηλικία, το μορφωτικό και επαγγελματικό επίπεδο καθώς και το μέγεθος του εισοδήματος και του συνολικού του πλούτου, τα αποτελέσματα

δείχνουν πως το επίπεδο ανάληψης κινδύνου διανέμεται μεταξύ των επενδυτών καθώς και πώς αυτό διαμορφώνεται και προσαρμόζεται μετά από κέρδη ή απώλειες. Ενδιαφέρον παρουσιάζει το γεγονός όπου αντίθετα με την παρούσα βιβλιογραφία, οι γυναίκες εμφανίζονται διαθέσιμες να αναλάβουν υψηλότερα επίπεδά κινδύνου από ότι οι άντρες, υπονοώντας έτσι ότι οι γυναίκες στην αγορά του ξένου συναλλάγματος διαφέρουν στατιστικά σημαντικά από τις γυναίκες στην αγορά των μετοχών. Ελέγχοντας το πως διαμορφώνεται και προσαρμόζεται ο κίνδυνος μετά από κέρδη ή απώλειες ξεχωριστά για τα δυο φύλλα, παρατηρείται η έκθεση των αντρών στην συμπεριφορική προκατάληψη, ονομαζόμενη ως "self-attribution bias". Δηλαδή η τάση να αποδίδουν επιτυχής συναλλαγές σε προσωπικές τους ικανότητες και ατυχές συναλλαγές σε εξωτερικούς παράγοντες (π.χ. κακή τύχη). Η φυλετική αυτή διαφορά εξαφανίζεται όταν συγκρίνουμε ισάξια δείγματα αντρών και γυναικών βάση των δημογραφικών χαρακτηριστικών τους. Χαρακτηριστικά που αντιπροσωπεύουν τους καλλιεργημένους επενδυτές παρουσιάζονται να μειώνουν την πιθανότητα έκθεσης στην προαναφερθείσα συμπεριφορική προκατάληψη.

Τέλος, στο τρίτο κεφάλαιο, αξιοποιώντας μια εξαιρετικά βραχυπρόθεσμη, πτώση στην τιμή της στερλίνας (the sterling flash crash), εξετάζονται πιθανές επιδράσεις στην δραστηριότητα και την συμπεριφορά των ανεξάρτητων επενδυτών, συνεισφέροντας με αυτό τον τρόπο στην βιβλιογραφία που διερευνά τους εξωγενής παράγοντες απόκτησης εμπειρίας. Η υπάρχουσα βιβλιογραφία στον τομέα αυτό, εξετάζει γεγονότα με έμμεση επίδραση στην επενδυτική δραστηριότητα των επενδυτών ενώ η παρούσα έρευνα, μελετά μια δραματική εξωγενή προσωπική εμπειρία με άμεση επίδραση στην επενδυτική τους δραστηριότητα.

Τα αποτελέσματα υποστηρίζουν την ασύμμετρη ανταπόκριση στον όγκο συναλλαγών που πραγματοποιούν οι επενδυτές την περίοδο μετά το γεγονός, η οποία στηρίζεται στην θέση που διατηρούσαν ανοικτή την ώρα του περιστατικού δηλαδή, κατά πόσο η υπάρχουσα τους θέση θεωρείτο κερδοφόρα ή ζημιογόνα. Μελετώντας πιθανές επιδράσεις του περιστατικού στην έκθεση των επενδυτών στην συμπεριφορική προκατάληψη, ονομαζόμενη ως "disposition effect"[1], δεν παρατηρείτε οποιαδήποτε ασύμμετρη ανταπόκριση στην συμπεριφορά τους, ωστόσο εμφανίζονται ενδείξεις γενικής αύξησης

[1] Disposition effect ορίζεται ως η συμπεριφορική προκατάληψη σύμφωνα με την οποία οι επενδυτές παρουσιάζονται λιγότερο πρόθυμοι να κλείσουν τις ζημιογόνες θέσεις τους σε σχέση με τις κερδοφόρες.

του επιπέδου έκθεσης στην αναφερθείσα συμπεριφορική προκατάληψη από όλους τους ενεργούς επενδυτές στην στερλίνα για την περίοδο μετά το περιστατικό. Το αποτέλεσμα αυτό υποδεικνύει πως μια απότομη, εξωγενής και στιγμιαία αλλαγή στην διακύμανση της αγοράς μπορεί να αυξήσει τα επίπεδα εμφάνισης της συμπεριφορικής προκατάληψης, disposition effect, των ανεξάρτητων επενδυτών.

Abstract

The trading activity, behavior and performance of individual investors is attracting the attention of market practitioners and academics with the latter group trying to identify patterns, strengths or weaknesses on their trading attitude and the former, by observing the pre-reported characteristics, trying to create a safe trading environment for them through continuously imposing and updating regulation restrictions. This project takes advantage of a proprietary intraday dataset on individuals trading activity in Foreign Exchange (FX) market and aims to extend our knowledge about retail investors behavior with the accomplishment of three empirical chapters.

Chapter one uses the aggregate of long and short positions of retail investors in EURUSD exchange market to examine the effects of news sentiment and scheduled macro news announcements on retail investors order flow. Evidence suggests a significant contrarian reaction of individual investors around scheduled macro news announcements which is reduced after controlling for past returns, indicating that retailers response is mainly generated due to their return contrarian disposition. In addition, making use of time series analysis and following predictive methodology, outcomes confirm individuals' return-contrarian behavior on an intraday basis as well as the predicting power of the rolling 30-minute lagged sentiment change on their trading activity. Statistically significant returns, resulting by using a simple cross-over trading strategy that generates signals opposite to investors net order flow, reveals that individual's contrarian behavior is not based on information, but adds value to the market through its liquidity provision role.

In the second chapter, the use of a disaggregated trade by trade data along with the investor characteristics allow for a second level of analysis to investigate possible differentiation of individuals risk-taking behavior by investor characteristics. An important novelty of the current project is the examination of investors' attitude towards risk, through the analysis of the leverage level that each investor is using, serving as a direct measure of risk. As existing literature proposed, young, educated investors, with higher employment status and very high income and net worth are willing to accept higher levels of risk. Moreover, Asian traders are generally engaged in greater risk levels, followed by Africans, Europeans, Americans and finally traders from Oceania. The willingness of women to accept higher levels of risk than men do, is an unexpected outcome suggesting that

women in FX market are significantly different from women in equity markets. When testing how men and women adjust their risk taking behavior based on past performance, evidence proposes that men exhibit self-attribution bias and women are not. Noted gender differences disappear after comparing matched samples based on demographic characteristics, indicating that behavioural differences on risk adjusted behavior mainly arise due to demographic variations and not gender per se. In particular, characteristics that literature suggest representing sophisticated investors are found to decrease the probability of exhibition of self-attribution.

The work on the behavior of retail investors is extended in the third chapter, through the usage of the sterling flash crash episode on October 7th, 2016, which is an exogenous market shock with a direct impact on investors trading activity to examine whether such an event can affect individuals future trading behavior. First, the results are showing a non-monotonic response on individuals trading volume and more specifically, a differential reaction based on the direction of investors exposure at the time of the incident. An analysis on traders' disposition effect indicates that overall, an instantaneous exogenous market shock can exaggerate the exhibition of the disposition effect of individual investors, contributing to the literature that investigates alterations of investor behavioural biases during periods of high uncertainty.

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General Introduction

Retail investors participation in FX markets was facilitated around 2000 when retail oriented platforms started offering online margin brokerage accounts to private investors (see Rime and Schrimpf, 2013). Since then retail investor trading in FX markets became a non-negligible part of the enormous FX market. The 2019 Triennial Central Bank Survey published by the Bank of International Settlements (BIS) reports that in April 2019 the average daily retail-driven turnover in the FX market is $201 billion representing 3% of the average daily total market turnover. The corresponding figure for insurance companies, pension funds and other institutional investors is at 12% and for hedge funds and proprietary trading firms at 9%.

Using a detailed proprietary dataset from a European regulated financial services firm that provides online trading services to retail investors, this research project aims to investigate several aspects of retail investor trading behavior in FX markets. It's crucial to identify retail investors' behavior, separated from other trader types (institutions, corporations, interdealer e.t.c), since retail investors are likely to differ in the quantity and quality of private information they possess as well as in their trading motives and trading strategies. Their trading behavior has been studied extensively in stock markets (see Barber and Odean, 2011 survey paper), but not in the FX markets with notable exceptions of Menkhoff et al. (2016), Heimer (2016), Heimer and Imas (2018), Ben-David et al. (2018) and Heimer and Simsek (2019).

Menkhoff et al. (2016), investigate the aggregate order flow of different FX end-users, including individual investors and provide evidence for their return contrarian trading behavior on a daily basis. The works of Heimer (2016), Ben-David et al. (2018) and Heimer and Imas (2018) mainly contribute to the behavioural finance literature, in which several behavioural biases have been identified among individual investors. Heimer (2016), examines the disposition effect on individual investors by first proving its existence on FX retail traders and then by showing an increase on the reporting bias as traders interact with each other on a social trading platform. Ben-David et al. (2018) provide evidence consistent with the exhibition of self-attribution bias on FX retail traders and specifically show that individuals in FX market tend to attribute successful outcomes to their own skill and unsuccessful outcomes to bad luck. Heimer and Imas (2018) and Heimer and Simsek (2019) utilize a proposal that restricts individuals' available leverage level and investigate their behavior around the event. The latter study shows that there is a 23% reduction on their average trading volume after the constrain, accompanying with an 18 percentage points increase on the monthly performance of high leverage traders'. The former supports that the increased performance arises basically from the lower exhibition of disposition effect and specifically the increased willingness of investors to realize losses after the amendment.

It's important to examine separately the behavior of retail investors in FX market from equity market since FX market differs in two major aspects. First and most importantly, the forex market offers the highest leverage level that an investor can obtain in financial markets and secondly, it's hard for retail investors to acquire access into private information which can significantly affect their trading attitude.

This project aims to extend our knowledge about retail investors behavior with the accomplishment of three empirical chapters:

- <u>Chapter 1:</u> The effects of news sentiment and scheduled macro news announcements on retail investors order flow in FX markets.
- <u>Chapter 2:</u> Heterogeneous risk-taking behavior among retailers in FX market.
- <u>Chapter 3:</u> Flash Crash: An exogenous determinant of individuals behavior in FX market.

Chapter one uses a proprietary intraday dataset of the aggregate long and short positions of retail investors in EURUSD exchange market to investigate the effects of news sentiment and scheduled macro news announcements on retail investors order flow. Order Flow is a signed trading volume and is estimated as the difference between the net long and net short initiated positions with a positive (negative) sign indicating a preference on buy (sell) orders. The contribution of this empirical study is threefold. First, while most studies concentrate on interdealer/interbank market order flow, the focus of this chapter is on retail investor order flow. Second, we analyze the effect of sentiment on the behavior of retail investors in FX markets and not on the overall pricing effect as in existing literature. And third, to capture market sentiment, the current project makes use of a new intraday sentiment measure, provided by Thomson Reuters Marketpsych Indices (TRMI).

The results suggest that individuals exhibit a contrarian behavior over the surprise of the scheduled macro news announcement which is mostly driven by their return-contrarian behavior rather than the surprise of the announcement itself. Further, making use of time series analysis and following predictive methodology, evidence support individuals' return-contrarian behavior on an intraday basis and the predicting power of the rolling 30-minute lagged sentiment change on their trading activity. Finally, the lack of informational trading on individuals activity is emphasized by the statistically significant returns generated with the employment of a simple cross over trading strategy, that produces buy and sell signals opposite to that indicated by individual investors net order flow. Reported findings indirectly imply that the importance of their contrarian behavior in the FX market is to provide liquidity to the market.

Chapter two expands our knowledge on the behavior of retail investors in FX market by providing a detailed examination of the attitude of retail investors toward risk. More specifically, it examines whether demographic factors such as age, gender, educational level, employment status, income, net worth and geographical region, differentiate investors willingness to accept risk as well as the way that past performance affects adjustments to their risk taking behavior. One of the paper's key innovations is the use of a direct measure of risk and that is the leverage level that each investor is using to trade. The forex market offers the highest levels that an investor can obtain in financial markets.

Aligned with the findings of existing literature, young, educated investors, with higher employment status and very high income and net worth are willing to accept higher levels of risk. Moreover, Asian traders are generally engaged in greater risk levels, followed by Africans, Europeans, Americans and finally traders from Oceania. What is not consistent with the literature is the fact that women appear to be more willing to accept higher levels of risk than men do, a result that is robust after comparing women with a control sample of men based on demographic characteristics. Then, by testing how men and women adjust their risk taking behavior after gains or losses, evidence suggests that male investors are prone to self-attribution bias while women are not. Demographically comparable samples of the two genders present the same behavior, implying that other demographic differences rather than the gender, determine the exhibition of the bias. Supplementary, characteristics representing sophisticated investors are shown to decrease the probability of exhibition of self-attribution.

Finally, chapter three uses the sterling flash crash episode which is an exogenous 200 standard deviation shock that hit the FX market on October 7th, 2016 and examines possible influence on FX retail investors trading behavior. During the flash crash, the British Pound suffered a sharp and short-lived price movement with the GBPUSD exchange rate plummeting to a three decade historical low, by losing around 9% of its initial value in less than a minute and with most of this fall to be reversed over the following ten minutes.

This paper contributes mainly to the literature that exploits the exogenous determinants of personal experience. Unlike related work on this area, chapter three takes advantage of the sterling flash crash incident, which can be considered as an exogenous dramatic trading experience event to investigate possible effects on individuals trading behavior. Existing literature focuses on exogenous dramatic life experience events, like a macroeconomic event, an outbreak of civil violence or a natural disaster such as earthquake, hurricane or tsunami. The use of an unpredictable event with a sharp drop in a remarkably short time period along with the availability of trade by trade data at an extremely fine scale and the short selling ease that represents FX market, enables the acquisition of a clear view on the asymmetric effect which can arise due to the event's occurrence.

Empirical results support the asymmetric response on individuals trading volume which differs based on their trading position at the time of the incident. By investigating the impact of the event on individuals disposition effect, there is no asymmetric influence on individuals with respect to their trading position, but there is an evidence of an overall increase of the investors' disposition effect in the post event period. Reported results are consistent with studies that analyse changes on investors behavioural biases during periods of high uncertainty with the current study providing evidence of exhibition of stronger disposition effect after an instantaneous, exogenous, market uncertainty shock.

Understanding what affects and what configures individuals trading behavior is of a great importance for retail investors and for supervisory authorities. Through the better understanding of their trading attitude, investors can minimize cost and improve their trading performance and policy makers can enhance if needed the formation of investors' regulatory protections.

Chapter 1

The effects of news sentiment and scheduled macro news announcements on retail investors order flow in FX markets.

Chapter 1: The effects of news sentiment and scheduled macro news announcements on retail investors order flow in FX markets

Abstract

This paper analyzes retail investor behavior in foreign exchange (FX) markets. Using a proprietary intraday dataset of aggregate long and short positions of retail investors in EURUSD for the period July 2014 to April 2016, along with a measure of intraday news sentiment provided by Thomson Reuters Marketpsych Indices (TRMI) and scheduled macro news announcements in both the US and Euro area, we find the following: First, we provide evidence consistent with the uninformed status of retail investors; second, we show significant reaction of retail investors around macro news announcements; and third, we find that lagged returns and news sentiment affect their trading activity on an intraday basis. More specifically, we present evidence that, after scheduled macro news announcements, individuals exhibit a contrarian behavior over the surprise of the announcement which is mostly driven by return movements rather than the surprise of the announcement itself, even though there is a news-contrarian tendency in positive surprise events. Further, we show a return-contrarian behavior on an intraday basis and the predicting power of the rolling 30-minute lagged sentiment change on their trading activity. Finally, with the use of a simple cross over trading strategy, we find that the contrarian behavior of individuals is not based on information, indirectly implying that individuals are helping in the stabilization of the market through their liquidity provision role.

1. Introduction

It's crucial to identify retail investors' behavior, separated from other trader types (institutions, corporations, interdealer e.t.c), since retail investors are likely to differ in the quantity and quality of private information they possess as well as in their trading motives and trading strategies. Even if we accept the fact that individual investors may be unsophisticated-noise traders (Kyle, 1985)[2], an aggregation of their trading activity may result in a significant influence in market movements (Barber et. al., 2008).

In this study we analyze the trading activity of retail investors in foreign exchange (FX) market and we investigate the effect of scheduled macro news announcements and news sentiment on retail investors' order flow[3]. We achieve this, by using a proprietary intraday dataset of aggregate long and short positions of retail investors in EURUSD for the period July 2014 to April 2016, along with a new intraday news sentiment measure provided by Thomson Reuters Marketpsych Indices (TRMI) and scheduled macro news announcements in both the US and Euro area.

Our study is motivated by two alternative literatures. The substantial literature on the effects of interdealer market order flow, on FX pricing, as well as the well-recognized literature on the effects of sentiment on market movements in general.

Semi strong form of efficient market hypothesis, an idea developed by Fama in the 1970s, motivated researchers to link assets' pricing movements to various sources of information. The magnitude of the impact on FX markets has been theoretically and empirically studied in several papers. Researchers are trying to understand and explain how announcements, "new" information, macroeconomic and microeconomic measures, influence FX return and volatility as well as the overall market activity.

The pioneer work of Meese and Rogoff (1983), on testing exchange rate movements using macroeconomic variables, and the failure of their empirical models to forecast exchange rates better than a random walk does, gave rise to an avenue in empirical literature, by measuring the effects of macro news on intraday exchange rate movements. Different empirical models and methodologies developed since then, in order to investigate the

[2] Kaniel et al. (2012) show that individual investors trading activity before earnings announcements, positively predict stock returns.
[3] Order Flow is a signed trading volume and is calculated as the difference between the net long and net short initiated positions. A positive (negative) sign indicates a preference on buy (sell) orders.

existence of this linkage. A key measure, for deeper understanding the link between announcements and exchange rate movements, is order flow. Evans and Lyons (2002a), innovators of this work, using tick by tick data on actual transactions for DM/USD and YEN/USD spot exchange rates, over a four-month period, found that order flow, does indeed matter for exchange rate determination.

Since order flow refers to signed trading volume, and trading volume refers to the way that market participants form their beliefs, expectations, risk preferences, their given information's interpretation and their general strategies, then order flow of corresponding participants can be considered as a proxy for their overall behavior. Hendershott et al. (2015), using institutional order flow as a quantitative measure of net trading by institutions, find evidence that order flow predicts news. Menkhoff et al. (2016), by investigating order flow of different FX end-users, found that, end-user groups show heterogeneous behavior in terms of trading styles and strategies as well as their exposures to risk and hedge factors. For example, they found that long-term demand-side investment managers tend to be positive feedback traders with regard to past currency returns, while individual investors tend to be negative feedback traders (contrarians).

There is a substantial literature trying to link investor sentiment with asset prices fluctuations, using several different proxies in order to capture sentiment. The idea that media can have significant impact on market movements have led to the development and usage of media content analysis in order to capture market sentiment/investors sentiment and explore this relation. Tetlock (2007), using daily content from the "Abreast of the Market" column of the Wall Street Journal, finds that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and unusually high or low pessimism predicts high market trading volume. Plakantaras et al. (2015) use StockTwits posts as a proxy for investor sentiment to forecast exchange rates through machine learning methods, while Smales (2014), Michaelides et al. (2015), Borokova and Mahakena (2015) and Sun et al. (2016) use as proxy for investors' sentiment the sentiment index developed by TRMI.

Our project contributes significantly to both aforementioned literatures. We contribute to the existing literature in three main ways. First, using high frequency data in FX market we examine retail investors' behavior. Order flow analysis has been focused on the interdealer/interbank market order flow and not on retail investor order flow. Menkhoff et al. (2016), investigate order flow of different FX end-users, including individual investors, on a daily basis. By allowing a wide window around the events under examination, it is more possible to simultaneously allow the effects of other news hitting the market to mutate or even modify the analysis results. By using 5-minute intervals we mitigate this problem. Second, we test sentiment effects on the behavior of retail investors in FX markets. Existing literature on this area, testing the effects of sentiment, as captured by different types of proxies, has concentrated on market pricing and not on the behavior of FX retail investors. Third, we rely on the TRMI to obtain our intraday sentiment measure, which is superior both coverage wise and time wise considering other sentiment proxies used in finance literature. Coverage wise, the TRMI indices are developed using a complex and sophisticated algorithm and scan the content of up to 3 million articles from news (premium newswires along with other sources available to professional investors) and social media (blogs, forums and tweets) scoring the text content. Time wise, the indicators are updated every minute for sectors, regions, countries, commodities and energy topics, indices and currencies. Sun et al. (2016), also use intraday TRMI sentiment to investigate the predictive relation between high frequency investor sentiment and stock market returns. They validated the interpretation of TRMI sentiment measure, by comparing it with three of the most widely used sentiment measures, the Baker and Wurgler (2006) investor sentiment index (BW), the University of Michigan consumer sentiment index (UM) and the investor sentiment proposed by Huang et al. (2015) – (PLS)[4]. In all three cases, they found that TRMI sentiment index moves in a similar pattern as with the three most widely used measures[5].

Therefore, the combination of a rich proprietary dataset on the trades of retail investors for a two-year period along with the richness of the intraday TRMI, extends the existing literature and contributes to it, since it provides an examination of the effect of scheduled macro announcements and news sentiment on the trading behavior of retail investors. To the extent of our knowledge, there is no other work that examines the effect of macro scheduled announcements and news sentiment on retail investors' order flow in FX markets. To do so, we use Net Order Flow, Net Long, Net Short and Overall Unsigned Volumes as proxies for retail investors' behavior.

[4] All three measures are available on a monthly frequency while TRMI are available on a minute by minute frequency.

[5] Michaelides et al. (2018) use TRMI sentiment in the forex market literature.

To test the effects of macro scheduled announcements on retail investors' behavior, we use standard event study methodology as well as panel regression analysis around positive and negative surprise events. The reported results in the pre-announcement windows are consistent with the uninformed status of the retail investors. More specifically, there is no significant abnormal reaction for Net Order Flow, Net Long and Net Short in the pre-event windows for both negative and positive surprise events. At the post-announcement periods we observe that retail investors exhibit a contrarian behavior over the surprise of the announcement align with the findings of Kaniel et al. (2012) who study individual investors trading activity around earnings' announcements and support that, at the day of the announcement, individuals' contrarian trading behavior arise basically from their return-contrarian behavior and not from the sign of the earning's surprise itself. After controlling for past returns, we find that individuals trading buy and sell preferences are mostly driven by returns movements rather than the surprise of the announcement, even though there is a news-contrarian tendency in positive surprise events.

To test the effects of news sentiment on retail investors' behavior, we make use of time series analysis where the dependent variable is the Net Order Flow and following predictive methodology, we include the lagged value of sentiment changes as an independent variable. In order to test the impact that returns may have on individual investors trading activity, we are also including in our models lagged values of the EURUSD exchange rate return. Results show a statistically significant linkage between sentiment and order flow, which remains robust even after controlling for the impact that macro variables can cause to Net Order Flow. Particularly, by testing the predicting power of news sentiment on retail investor order flow we find that the rolling 30-minute sentiment change, strongly predicts their trading behavior. Coefficient estimates of the lagged EURUSD exchange rate returns indicate the return-contrarian behavior of individual investors on an intraday basis, a behavior which was also documented by Menkhoff et al. (2016) by using daily data.

In an attempt to examine whether there is any information about future FX returns on the aggregate individuals investors trading, we deploy a simple cross over trading strategy, that generates buy and sell signals opposite to that indicated by individual investors Net Order Flow. More specifically, the strategy generates a sell signal when the short term moving average of Net Order Flow crosses above the long term moving average of Net Order Flow and a buy signal when the short term moving average of Net Order Flow crosses below the long term moving average of Net Order Flow. By estimating the mean and median returns for different holding periods, the strategy yields statistically significant returns for almost all tested holding periods for both, in-sample and out-of-sample analysis.

The aim of this analysis is not to investigate the relative performance of various trading rules and strategies and propose a money-making trading strategy that maximizes profits. The fact that the trading strategy generates positive results both in-sample and out-of-sample, implies the uninformative content of the contrarian trading of individuals, indirectly suggesting that their existence add value to the market through their liquidity provision role.

For investors, understanding how macro scheduled announcements and news sentiment affect their behavior, can help them to minimize costs (avoid trading during time periods where other trader types are more possible to have private information) and improve their trading performance. For Financial Services Firms that provide online trading services to retail investors, it’s important to understand the link between their clients’ behavior and macro scheduled announcements, since this can help them to improve the trading services and guidance provided to clients and also hedge their exposure that is being produced by individuals trading activity. Finally, for policy makers, understanding how individuals form their trading decisions and what influences their trading strategies, can help them to assess and improve if needed the efficacy of investors’ regulatory protections.

The remainder of the paper proceeds as follows. Section 2 presents a literature review on FX linkage to news, while the major hypotheses of this study are also highlighted. Section 3 describes the dataset and measurement of variables. Descriptive statistics also are included in this section. Section 4 describes the methodology and Section 5 presents the empirical results. Finally, Section 6, summarizes the major conclusions.

2. Literature Review and Hypotheses Development

2.1. Literature Review

A number of researchers, examining exchange rate movements using a variety of macroeconomic variables, found that no empirical model will ever explain a high percentage of the variation in the exchange rate. In other words, no empirical model predicts exchange rate movements better than a random walk does (Meese and Rogoff, 1983, Flood and Rose, 1995 and Cheung et al., 2005). This pioneering work of Meese and Rogoff (1983), which was developed by using monthly data, gave rise to an avenue in empirical literature, measuring the effects of macro news on intraday exchange rate movements.

Studies, attempting to test the hypothesis that the surprise component of announcements is able to move exchange rates on an intraday basis, do find statistical and significant support for the hypothesis. Moving one step forward and taking these results as a benchmark, researchers are trying to deeper understand the link between announcements and exchange rate movements, and answer questions like which announcements actually affect those movements, how quickly and in what extend they do and if this influence remains constant over time, over countries and over different clustering of surprises (good news vs bad news).

For example, employment report[6] and monetary policy[7], are the type of announcements that have consistently demonstrated to have statistical and significant impact on exchange rate movements. Another announcement classification impact tested on exchange rate is the scheduled vs unscheduled classification[8]. Almeida et al. (1998), who studied the behavior of DEM/USD exchange rate around scheduled and unscheduled announcements, found that market incorporate the information from scheduled announcements more quickly than the information from unscheduled announcements. They accredit this quicker reaction to the fact that in the case of scheduled news, agents have time to form expectations and strategies for each possible sign of the surprise component. Dominiguez and Panthaki (2006), using a broader classification of news, suggest that, future models of exchange rate should include both, scheduled and unscheduled fundamental news as well as non-scheduled non fundamental related news, since they also influence exchange rates.

The impact of news is shown to be time-varying in the sense that the order and the timing[9] of related announcements is important. Furthermore, empirical evidence suggests the existence of asymmetries between good and bad news events and between US and other

[6] See Edrington and Lee (1996) and Almeida et al. (1998).
[7] See Engel and Frankel (1984), Ito and Roley (1987), Edrington and Lee (1996), and Rosa (2013)
[8] See also Bauwens et al. (2005) and Evans and Lyons (2008).
[9] See Almeida et al. (1998), Andersen and Bollerslev (1998) and Ehrmann and Fratzsher (2005).

country news events[10]. A use of all of the above is in the Andersen et al. (2003) study. Using a 5-minute sample data and by jointly modeling conditional mean and conditional variance, the authors empirically examine the relation of price discovery of FX rate. Firstly, they show that conditional mean adjustments of exchange rates to news occur quickly in contrast to conditional variance adjustments and that an announcement's impact depends on its timing relative to other related announcements and on whether the announcement time is known in advance. They also show that, the surprise component of US announcements, has a greater impact on the US$/CN$ exchange rate than the Canadian one. They extend existing literature by observing an asymmetric reaction based on the sign of shocks. They find evidence that, bad news has stronger impact than good news.

A key measure, for a deeper understanding of the link between announcements and exchange rate movements[11], is order flow. Traditional macro modeling literature of FX rate determination argues that only fundamental macro surprises can explain exchange rate movements, in an environment where all information is publicly available and immediately incorporated into prices. Studies have shown that even if the same information is available at the same time to all market participants; their heterogeneous interpretation can cause a delay to price adjustments[12]. Since, macroeconomic announcements can cause this complex and diverse interpretations, researchers attempt to clarify the relationship between announcements and exchange rate movements, using a micro level price determinant, the order flow. Evans and Lyons (2002a), innovators of this work, using tick by tick data on actual transactions for DM/USD and YEN/USD spot exchange rates, over a four-month period, found that order flow, does indeed matter for exchange rate determination. They provide further support for their statement by reinvestigating the existence of this link, using another set of spot exchange rate (Evans and Lyons, 2005 – use USD/EUR), a broader group of macroeconomic announcements (Evans and Lyons, 2008), and by testing whether the effects of order flow in a given currency market is impounded

[10] See Almeida et al. (1998), Andersen and Bollerslev (1998), Faust et al. (2003) and Love and Payne (2008).
[11] Order flow linkage to FX movements has been extensively discussed in several papers. See for example, Cai et al. (2001) , Lyons (2001), Evans and Lyons (2002a,b,c), Evans (2002), Rime (2003) , Andersen et al. (2003), Osler (2005), Evans and Lyons (2005, 2006) and Danielsson & Love (2006), Dominguez and Panthaki (2006), Evans & Lyons (2008), Berger et al. (2008), Love and Payne (2008), Phylaktis and Chen (2010) , Rime, et al. (2010), Evans & Lyons (2012), Menkhoff, et al. (2016) .
[12] These types of public news, along with, the private types of news, have been defined by Evans (2002) as Non Common Knowledge (NCK) news.

in other currency markets (Evans and Lyons, 2002c) – they called this informational integration).

Since order flow refers to signed trading volume, and trading volume refers to the way that market participants form their beliefs, their expectations, their risk preferences, their given information's interpretation and their general strategies, then order flow of corresponding participants can be considered as a proxy for their overall behavior. Hendershott et al. (2015), using institutional order flow as a quantitative measure of net trading by institutions, find evidence that order flow predicts news. Menkhoff et al. (2016), by investigating order flow of different FX end-users, found that, end-user groups show heterogeneous behavior in terms of trading styles and strategies as well as their exposures to risk and hedge factors. For example, they found the long-term demand-side investment managers tend to be positive feedback traders with regard to past currency returns, while individual investors tend to be negative feedback traders (contrarians). Menkhoff et al. (2016) results, about the individual investors' contrarian behavior, squares well with the results of Kaniel et al. (2008), who also show that individuals trade as contrarians, stating that such behavior provides liquidity for institutional investors. As supported by Kyle (1985), individual investors are more likely to be uninformed, irrationally act on noise, and are often characterized as noise traders. Both, Kaniel et al. (2008) and Barber et al. (2009) by using order imbalances of individual investors provide evidence that retail investors trading activity positively predicts returns over short horizons, with the stocks that heavily bought to outperform the stocks that are heavily sold.

DeLong et al. (1990) by separating investors into two groups, rational arbitrageurs and irrational noise traders, show that irrational noise traders' sentiment can cause prices to depart significantly from fundamental values. There is a substantial literature trying to link investor sentiment with asset prices fluctuations. Models of investor sentiment in stock markets such as DeLong et al. (1990) predict that, low sentiment will generate downward price pressure and unusually high or low values of sentiment will generate high trading volume.

Several different proxies have been developed in order to capture sentiment[13]. The idea that media can have significant impact on market movements have led to the development

[13] See Zweig (1973), Lee et al. (1991), Neal and Wheatley (1998), Baker and Stein (2004), Baker and Wurgler (2006), Baker and Wurgler (2007), Baker et al. (2012), Kelly and Pruitt (2014), Huang et al. (2015) or survey

and usage of media content analysis in order to capture market sentiment/investors sentiment and explore this relation. Tetlock (2007), using daily content from the "Abreast of the Market" column of the Wall Street Journal, finds that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and unusually high or low pessimism predicts high market trading volume. Extending their analysis, using negative words in all Wall Street Journal (WSJ) and Dow Jones News Service (DJNS) stories about individual S&P 500 firms, Tetlock et al. (2008), found significant impact of their quantitative measure of media language, on firms' accounting earnings and stock returns. Azar and Lo (2016) use tweeds referencing the Federal Reserve ahead of Federal Open Market Committee (FOMC) meetings to predict future stock market returns. Plakantaras et al. (2015) use StockTwits posts (a message board dedicated to finance) as a proxy for investor sentiment to forecast exchange rates through machine learning methods, while Smales (2014), Michaelides et al. (2015), Borokova and Mahakena (2015) and Sun et al. (2016) used as proxy for investors' sentiment the sentiment index developed by TRMI. Peterson (2016), provide evidence that news' sentiment can have a large impact on market movements.

2.2. Hypotheses Development

In this section, we motivate and develop the paper's central testable hypotheses, the content of which can be condensed into two main components. Firstly, we hypothesize that retail investors react to macro news announcements and secondly, returns and news sentiment significantly affect retail investors' order flow.

Most traditional models assume two types of traders, informed traders and uninformed traders. Informed traders can be characterized as those traders who may have access to valuable private information for an upcoming announcement. Alternatively, uninformed traders are unaware of any kind of non-publicly available information before the actual release. From the early work of Kyle (1985) and Glosten and Milgrom (1985), researchers generally agree that informed traders exploit their informational privilege and realize profits at the uninformed traders' expense. Chae (2005), supports that due to the fluctuations of information asymmetry before scheduled announcements, uninformed

based proxies like the University of Michigan Consumer Sentiment Index and the American Association of Individual Investors (AAII).

investors will reduce their trading activity and increase it thereafter. Particularly, they ascribe the decrease in trading volume before the event, to the existence of higher information asymmetry (informed investors have an informational advantage over uninformed investors) and the increase on the trading volume after the event, to the existence of lower information asymmetry. Their explanation stands in contrast with the findings of Kim and Verrecchia (1994), who argue that after news events, information asymmetry is high due to heterogeneous interpretations of the content of the announcement and the existence of informed investors, in the sense that some investors have the ability to better interpret the implications of public news announcements.

Even if, as Lyons (2001) supported, it's difficult for traders to directly acquire private information for the content of the macroeconomic announcements[14], an indirect source of private information can arise through the observation of interdealer order flow[15]. Since the announcements under examination, are the scheduled macro news announcements, for which the timing of the release can be estimated in advance (for informed and uninformed investors, this is publicly available information), if retail investors, who are mainly considered as uninformed investors, realize that there is a place for informed traders, we will expect that their overall trading activity will decrease before the announcement in order to avoid transactions with informed counterparties. After the release of the announcements, since the content of it is no longer hidden, we will expect an increase on their overall trading activity as a response to new information.

Hypothesis 1: *Retail investors' overall activity decreases before macro news announcement and increases right after.*

Furthermore, even if prior literature provides evidence of significant reaction ahead of scheduled FOMC announcements, there are no studies that prove the existence of informed trading before other major macro news announcements. For example, Lucca and Moench (2015) and Bernile et al. (2016), by investigating the reaction of equity markets around different types of macro news' announcements[16], identify informed trading ahead

[14] There are studies that show market reaction ahead of macro news announcements, and most specifically, ahead of FOMC announcements (see Lucca and Moench (2015), Bernile et al. (2016) and Karnaukh (2016)).
[15] In Section 2.1., there is a detailed report on the studies investigating the link between order flow and FX movements.
[16] Lucca and Moench (2015) use nine different types of macro news announcements. They use: Total Nonfarm Payroll

of FOMC announcements but not ahead of the other types of macro news announcements under examination. This brings us to Lyons (2001) argument, according to which it's difficult for any trader to directly acquire private information for the content of the macroeconomic announcements. In response, for retail investors who are mainly considered as uninformed investors, it's not anticipated that they will be able to analyze and predict the sign and magnitude of the surprise component.

Hirshleifer et al. (2008) examine the trading behavior of individual investors in the post earnings announcements period and test whether naïve individual investors are somehow responsible for the existence of the post-earnings announcement drift phenomenon. More precisely, they support that the drift exists, if naive investors trade in the opposite direction of the earnings surprise and consequently in the opposite direction of the institutional investors trading, therefore, individual investors will trade as contrarians to earnings surprises. Using actual individual investors trade, the authors test this hypothesis, named as individual trading hypothesis, and find no evidences supporting their conjecture. Kaniel et al. (2012), also investigate individual investors trading in post earnings announcements period and show that individual investors, after the announcement, trade as news contrarians. Based on these findings we expect a negative correlation between individual investors intraday order flow and announcement content at the post announcement period.

Hypothesis 2*: Individual investors order flow is inversely associated with the sign of the surprise only after the announcement.*

Moreover, Kaniel et al. (2008), Kaniel et al. (2012) and Menkhoff et al. (2016), use data on the stock and FX market on a daily basis and show that individual investors trade as return -contrarians. Thus, we also expect a return- contrarian trading behavior on an intraday analysis.

Hypothesis 3: *Individual investors exhibit a return-contrarian trading activity.*

Finally, the linkage of individual investors sentiment to market movements has been discussed in several papers, with controversial conclusions for the direction of the effect.

Employment, Initial Claims for Unemployment Insurance, the Advance GDP, the Institute for Supply Management's (Ism) Manufacturing Index, Industrial Production, Housing Starts, Producer Price Index, Consumer Price Index and Personal Income. Bernile et al. (2016) use three types of macro news announcements. They use: Nonfarm Payroll, Producer Price Index and GDP.

For example, Kumar and Lee (2006) and Schmeling (2007), use equity market data and investigate the effects of sentiment at an individual investor's level, with the first one supporting a positive sentiment-return relation and the latter a negative one. Kumar and Lee (2006) to proxy investors sentiment use the individual investors buy-sell imbalances whereas Schmeling (2007) extract the sentiment measure using individuals survey data. Menkhoff and Rebitzzky (2008) also use survey sentiment to proxy individual investors sentiment and test its influence on major foreign exchange market returns, including EURUSD. Reported results show that in the short run, investors sentiment does not correlate with future exchange rate returns. We are aiming to investigate whether sentiment that derives from news can be considered as a determinant of individual investors net order flow. News sentiment is found to significantly influence market returns[17] and overall media overage found to significantly affect individual investors trading activity. For instance, in Barber and Odean (2007) study, the authors examine the individual investors daily buy-sell imbalances and show that individual investors are net buyers of attention-grabbing stocks. They are splitting their stocks into those for which there is a news' story and those with no news and they provide evidence that individual investors are much more likely to be net buyers of stocks that are in the news rather than those that are not. Joe, Louis and Robinson (2009), analyze how media exposure of board ineffectiveness[18] affects the behavior of various economic agents, including individual investors and they provide evidence of negative reaction of individual investors to the media exposure. Further, Miller and Shanthikumar (2010) and Engelberg and Parsons (2011), investigate responses on individual investors trading volume, to local and non local news with both studies presenting a stronger reaction of local investors to local news. Following the important link among media coverage and equity investors trading activity, we expect a significant relation between news sentiment and FX retail investors signed trading volume.

Hypothesis 4*: News sentiment has a significant effect on individual investors order flow.*

[17] See for example, Tetlock (2007); Tetlock et. al. (2008) and Engelberg and Gao (2011).

[18] To proxy board ineffectiveness, they are using the news articles reporting the firms with the worst boards.

3. Data, Measurement of Variables and Descriptive Statistics.

Next, I describe the data sources and data collection procedures, and briefly outline the definitions and the summary statistics for the main variables of interest.

3.1. Dataset

Our dataset consists of three levels of data. The first level of data contains aggregate retail customer minute by minute buy and sell open interest volume from 10th July 2014 18:25 (EET) to 30th April 2016 23:59 (EET), for one of the major currency pairs, the EURUSD. The data were provided by a European Regulated Financial Services Firm[19] that provides online trading services to retail investors. The second level of our data, contains macro news' information regarding both, Eurozone (EU) and the United States (US). All relevant information has been collected from Datastream (Thomson Reuters). Finally, our third level of data, comprises the innovative, Thompson Reuters Marketpsych Indices (TRMI). TRMI analyzes news and social media data and convert their overall diction into comprehensive emotional indicators.

The main analysis is conducted using 5-minute intervals. Thus, data is converted by picking up the observations every five minutes, starting from midnight. Each day has 288 points. Forex market is open 24 hours per day, therefore, from 10th July 2014 18:25 (EET) to 30th April 2016 23:59 (EET), we have overall, 190,147 observations of 5-minute data. Technically, forex market is open 24 hours per day and 7 days per week. Nevertheless, the majority of dealers are choosing to close operations on weekend, leading on a very thin liquidity during that time. Normally, dealers providing trading services to retail investors, fall into this category. Since, we are analyzing retail investors' trades, we remove weekends from our data. Therefore, we end up with 135,715 observations[20].

[19] There are approximately five thousand active investors per day. Since it was founded, more than 1.5 million investors from more than 150 countries choose this firm for their active trading. Around 84% of traders in our sample have an educational level up to a bachelor's degree and an annual income less than €50,000. The actual name of the data source cannot be revealed due to a related agreement with the firm.

[20] Even after removing form our sample holidays like Christmas days (24th – 26th of December), New Year days (31st of December – 2nd of January) and Easter days (Friday before and Monday after Easter), there are no qualitative differences.

3.1.1. Buy and Sell Open Interest

We obtain the long and short exposure of the European Regulated Financial Services Firm, from its clients' side. The dataset contains aggregate retail customer, minute by minute, long and short open interest from July 2014 to April 2016. The positions are given in euro-money terms. For example, if an investor places a long (short) order for EURUSD, the size of the corresponding trade in euro money terms, will be incorporated in the firm's database, as long initiated position (short initiated position) at the date-time that the position opens. When the order is closed, that is when the investor takes the opposite position, the trade will not be incorporated in the database as short initiated position (long initiated position), since this is not considered as an initial trade. At the date-time the position closes, there will be a decrease in the exposure of the corresponding aggregate initiated position.

3.1.2. Announcement Data

The macro news' announcements were collected from Datastream (Thomson Reuters). The Database contains real time data for the macro announcements. Particularly, it includes per Country and per Classification, the Event Name, the exact date-time of the release, the measurement unit for each event, the actual, the prior of the actual and the expected value of the announcement. Expected value is given few days prior to the announcement, and it is denoted as Reuters Poll. It is calculated as the median of Reuter's analysts' forecast values. Reuters' analysts are Economic Research Houses, Credit Rating Agencies, Brokers, Banks and other specialist contributors around the world. The expected value is not available for all announcements.

We filter from the database, the announcements from United States and Eurozone and in order to test our hypothesis, we use the announcements which have been used by earlier studies. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events. Since in our sample period we include decisions for which monetary policy does not change[21], in order to identify surprise component of monetary policy decisions we are using the standard methodology employ in Kuttner (2001). The Kuttner surprise measure is the change in the

[21] Therefore, we receive zero surprises almost for all of the FOMC and ECB monetary policy announcements.

30-day federal funds futures (3-month Euribor futures) on days when Federal Open Market Committee (Governing Council for ECB) meets, to set its monetary policy. For all other macro news' announcements, we estimate the surprise component as the difference between actual and expected value. Therefore, events of which their surprise component, represent more economic growth in terms of domestic economy, have been defined as positive on the domestic currency events. If a reverse connection holds, they have been defined as negative on the domestic currency events.[22] We then adjusted the definition of positive and negative surprise events, in terms of their effects in the movement of EURUSD exchange rate[23]. Previous studies, like Bauwens et al. (2005), define announcements leading to more inflation than expected as negative events in terms of domestic economic growth. In our study, since we are investigating a period of worryingly low inflation, a possible positive surprise component in an inflation related announcement, would trigger a positive signal for the economic growth. Rosa (2013) also supports the positive relation between an increase in inflation and currency movement. This is also consistent with the argument of Love and Payne (2008), that the influence of same type of macroeconomic announcement may be different from region to region, since policymakers expectations, in each territory, are not the same[24]. Table 1 lists all the news' categories included in our sample. We present this news per country and per classification, the announcements name and the sign of the announcements effect in terms of domestic economic growth.

3.1.3. Thompson Reuters Marketpsych Indices

We use Thomson Reuters MarketPsych Indices (TRMI) to capture our news sentiment data. The need of understanding the psychological nature of the market, lead Thomson Reuters and MarketPsych LLC, to develop the TRMI. The indices use a complex and sophisticated algorithm, which overcomes the lexical ambiguity problem, by scoring the content of

[22] E.g. a positive surprise component for the EU GDP (US GDP) indicator, represents more growth for EU(US) economy, hence this is a positive event for the domestic economy, EU(US) and this could lead in an appreciation on the domestic currency, euro (dollar). A positive surprise component for the EU Unemployment report (US Unemployment report), represents less growth for EU (US) economy, hence this is a Negative Event for the domestic economy, EU (US) and this could lead in a depreciation on the domestic currency, euro (dollar).

[23] A positive event in EU (negative event in US), represents an appreciation of EURUSD exchange rate, therefore, this is a positive surprise event, while a negative event in EU (positive event in US), represents a depreciation of EURUSD exchange rate, therefore, this is a negative surprise event for the EURUSD exchange rate.

[24] Specifically, they document that, an increase in US inflation tends to cause the USD to depreciate, which is consistent with a monetary model of the exchange rate, while an increase in UK inflation tend to cause an appreciation on GBP, which is consistent with inflation targets of UK monetary authorities.

scanning text, based on its overall diction and not on the diction of words and phrases in isolation. The indicators are updated every minute for sectors, regions, countries, indices, currencies, commodities and energy topics with over 2 million articles operating daily.

TRMI include scores on more than fifty emotional indicators and topics, such as stress, gloom, fear, trust and joy as well as buzz metrics that indicate how much something is talked about. The minute by minute value of each TRMI emotional indicator, is a simple average, of the past 24 hours (1440 minutes) reported information. The indices are normalized with a scale between -1 to 1 or 0 to 1, corresponding to bipolar and unipolar indices. In this study we use both EU and US country sentiment indices. Sentiment index is defined as the net difference between the positive and negative references of all emotional indicators and topics, regarding the corresponding country.

3.2. Definition and Measurement of the Variables

In order to evaluate the behavior of individual investors around scheduled macro announcements and examine the effects of returns and news sentiment on their trading activity, we employ three main variables: Net Order Flow, Overall Unsigned Volume and Changes in Sentiment. Their detailed description is given below.

3.2.1. Net Order Flow

Net Order Flow is a signed trading volume and is calculated as the difference between the Net Long and Net Short initiated positions[25], in terms of volume of the base currency. That is, the change on the volume of initiated trades in terms of euro. A positive Net Order Flow either means that net buys were more than net sells or that the decrease of changes in buys was less than the decrease of changes in sells. For announcement i and date-time t, the raw Net Order Flow is given by:

$$\textbf{Net Order Flow}_{\mathbf{i,t}} = \text{Net Long}_{i,t} - \text{Net Short}_{i,t} \tag{1}$$

[25] Changes in the long and short open interest, provide measures of the Net Long and Net Short positions per five minutes, respectively. For example, $Net\ Long_{i,t} = Long_{i,t} - Long_{i,t-1}$. Hence, positive (negative) Net Long indicates that the exposure on the Long position has increased (decreased) within five minutes. In other words, individual investors, exhibit on average a positive(negative) view on the EURUSD exchange rate.

3.2.2. Overall Unsigned Volume

The sum of the absolute Net Long and the absolute Net Short positions provide a measure of overall trading volume/intensity and we denote it as Overall Unsigned Volume[26]. For announcement i and date-time t, the Overall Unsigned Volume is given by:

$$\textbf{Overall Unsigned Volume}_{i,t} = ABS\ |\text{Net Long}_{i,t}| + ABS\ |\text{Net Short}_{i,t}| \quad (2)$$

3.2.3. Changes in Sentiment

The minute by minute value of each TRMI sentiment score (emotional indicators), is a simple average, of the past 24 hours reported information, therefore there is a high persistence of first order autocorrelation, which we can dramatically reduce by simply concentrating on the changes in the TRMI sentiment score rather the raw values. Changes in TRMI sentiment at t, ΔS_t [27], is measured as the difference in raw TRMI sentiment data between time t and t-1.

$$\mathbf{\Delta S\_EU}_t = Sent\_EU_t - Sent\_EU_{t-1} \quad (3)$$

$$\mathbf{\Delta S\_US}_t = Sent\_US_t - Sent\_US_{t-1} \quad (4)$$

where $Sent\_EU_t$ ($Sent\_US_t$) refers to the raw TRMI EU (US) sentiment data at time t.

Since we are interested in testing the effects of sentiment on individual investors order flow, we use the relative EU to US sentiment change. To capture the relative EU to US sentiment change we construct and test the impact of the difference between EU and US sentiments, which is given by:

$$\Delta S\_EUvsUS_t = \Delta S\_EU_t - \Delta S\_US_t \quad (5)$$

where ΔS_EU_t (ΔS_US_t) is the EU (US) change in TRMI sentiment at time t.

Following Sun et al. (2016), who found that lagged half-hour sentiment change impact stock market returns, we use the rolling 30-minute lagged sentiment change to test sentiment impact on FX-retail investors Net Order Flow.

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[26] Our Overall Unsigned Volume measure is understated. This is because, if we assume that during a 5-minute interval, five new long positions were placed and at the same time five already opened long positions were closed, then their will be no Net Long change where actually there were 10 trades.

[27] Changes in TRMI sentiment, ΔS_t, find to be stationary time series data.

3.3. Descriptive Statistics

Table 2 reports descriptive statistics for the Long and Short initiated positions, the Net Long and Net Short initiated positions, the Net Order Flow, the Overall Unsigned Trading Volume, the 30-minute, EU vs US sentiment change and the EURUSD Return. All variables are measured at a 5-minute frequency. On average, the amount of open long initiated positions was around 102 million euro while the amount of open short initiated positions was around 125 million euro. Also, the long initiated positions open interest, range from 24 to 316 million, while short initiated positions open interest, range from 26 to 363 million. We can see a higher interest on Short initiated positions which it's also evident by observing the Net Long and Net Short mean values. The negative number of Net Long mean variable and the positive Net Short mean variable, indicates that, within five minutes, on average, investors are exhibiting a euro selling pressure. We can see that the Net Order Flow measure captures this tendency by the negative mean value of 2,905.22. The mean of Overall Unsigned Volume is closed to €2 million. The 30-minute EU vs US sentiment change takes values from -0.0445 to 0.0428 with zero mean and median.

The EURUSD Return, ranges between -1.51 and 1.66. Mean, median and skewness are close to zero (skewness is -0.3325 and is not tabulated) pointing to a symmetric EURUSD returns' distribution.

3.4. Seasonality

Intraday FX data are shown to exhibit strong seasonal patterns[28]. Omission of seasonality adjustment can lead to misleading statistical inference. Figure 1 shows the time of the day seasonal pattern while Figure 2 shows the day of the week seasonal pattern. To identify the seasonal patterns, we are using the average of the overall trading volume[29]. Graphs for the average of the long trading volume and the average of the short trading volume, were also plotted and same patterns were observed[30]. In our empirical analysis we control for seasonality.

[28] See Melvin and Yin (2000).
[29] Overall trading volume is the sum of long and short positions at time t.
[30] The graphs of the totals also plotted and similar patterns were observed.

4. Methodology

4.1. The Event Study Methodology

In our research, we use standard event study methodology to evaluate the behavior of individual investors around scheduled macro announcements. We use Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors' aggregate trading behavior. For analysis purposes, using the announcements' surprise component, we classify them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.). We then measure cumulative abnormal values over certain periods and provide a short – run overview, of the way that public information influences our variables of interest, pre, around and post the event.

An abnormal value is defined as the actual value of the variable of interest over the event window, minus the expected value over the event window. The expected value is the one that would have occurred in the case where an event did not take place.

For announcement i and date-time t the abnormal value is given by:

$$AV_{it} = V_{it} - E(V_i) \tag{4}$$

where, AV_{it}, V_{it}, and $E(V_i)$ are the abnormal, actual, and normal values respectively for time period t.

Like Chae (2005), we use the constant mean method for estimating the expected value of the variable under examination. According to this method, expected value equals to the mean value of the variable of interest, over the period covered over the estimation window. So,

$$E(V_i) = \frac{\sum_{t=t_1}^{t_2} V_{i,t}}{n} \tag{5}$$

where, $[t_1,t_2]$ is the estimation window and n is the number of observations included in that window.

The event window is defined as the 2-hour window around the event, one hour before the event[31], until one hour after the event (i.e. 25 observations of a 5-minute frequency). As

[31] As "event", we define the exact date-time of the announcement.

estimation window, we define the period, 3 hours before the event to 1 hour before the event.

To get accurate and interpretable results, we drop from our sample overlapping events. Particularly we exclude events that conflict with other events, either in the event or estimation window. In such cases, we take into consideration only the first one, in order to avoid possible biased abnormal values.

The cumulative abnormal values (CAVs) equal the sum of each announcements abnormal value over different sub – periods, pre, around and post an event.

$$\mathrm{CAV_i} = \sum_{t=t_1}^{t_2} \mathrm{AV_{i,t}} \qquad (7)$$

where, $[t_1,t_2]$ refers on the different sub – periods, under examination.

After estimating the CAVs variable for each announcement included in our sample, we apply a non-parametric statistical test (Wilcoxon signed-rank test), over certain periods before, during and after events, using the grouping for our news announcements as described in Section 3 (3.1.2). With the non-parametric test, we examine the hypotheses:

H_0: $Median\_CAV_j = 0$ vs H_1: $Median\_CAV_j \neq 0$

where, j is the analogous announcements' grouping and $Median\_CAV_j$, is the median of the CAVs included in the j grouping. Rejection of the null hypotheses leads to the conclusion that the events under examination, in group j, have a significant impact on the corresponding variable.

4.2. Panel Regression Analysis

To address heteroscedasticity and autocorrelation concerns and to control for different stable characteristics like the origin of our events or time-invariant variables, we conduct panel regression analysis without and with fixed effects.

In order to evaluate the behavior of individual investors around scheduled macro announcements, we estimate panel regressions using 5-minute frequency data, starting 3 hours preceding each announcement and ending one hour following each announcement. To examine the behavior of investors around different time periods of the event, we create dummy variables taking the value of 1 on the event relative time of interest and 0 otherwise. E.g. let's say we are interested to see their behavior at time period [+10min, +20 min], that is 10 minutes after the announcements to 20 minutes after the announcement, we create a dummy that takes the value of 1 when relative time equals to +10, +15 and +20 minutes and 0 otherwise. For each version of the model, we create dummies that span the whole event window [-60, +60] and that capture pre-event, at event and post event reactions of the dependent variable[32].

Thus, to empirically analyze individual investors behavior linkage with scheduled macro announcements, we include in our model as dependent variable, Net Order Flow and as independent variables the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags used was determined by using the Schwartz and Akaike information criteria. For robustness reasons, five versions of panel regressions are conducted: (a) with robust (White) standard errors clustered by event and no fixed effects, (b) with robust (White) standard errors clustered by event and country fixed effects, (c) with robust (White) standard errors clustered by event and day of the week fixed effects and (d) with robust (White) standard errors clustered by event and hour fixed effects and (e) with robust (White) standard errors clustered by event, country fixed effects and controls for seasonality (day of the week and hour of the day).

4.3. Time Series Analysis

To test whether returns and news sentiment impact individual investors' behavior, we make use of time series analysis where the dependent variable is the Net Order Flow and as independent variable following predictive methodology, we include the lagged values of the EURUSD exchange rate and lagged value of news sentiment change. As a proxy for news sentiment, we use the EU and US country level sentiment indices, as captured by TRMI, and construct the relative EU to US sentiment change as described on section 3.2.3.

[32] Robustness checks are also conducted by using longer estimation windows; 4 hours before the event to 1 hour before the event and 6 hours before the event to 1 hour before the event. Beyond testing different estimation windows, we are also using different standardization methods for our variables of interest. At first, we use Barber and Odean, 2008, standardization method according to which we estimate the standardize measure of abnormal value of the variable of interest, by subtracting the rolling 1-week-mean value of the corresponding variable and dividing by its 1-week-standard deviation, $\frac{V-\bar{V}}{\sigma}$. Instead of rolling 1-week-mean and 1-week-standard deviation, we are also using the rolling 1-month-mean and 1-month-standard deviation respectively. Secondly, we employ Menkhoff et al. (2016), standardization approach where we divide the Net Order Flow by its 1-week-standard deviation. Again, we also use the rolling 1-month standard deviation.

In addition to the independent variables mentioned above, we also include in our model dummy variables capturing the macroeconomic announcements relative time ([-60min,+60min]), to control for the effect that macroeconomic announcements can cause on individuals investors' Net Order Flow. In addition, in order to control for the effect that past levels of the dependent variable (Net Order flow) could have on its current level (and avoid omitted variable bias), we also add in our model lags of our dependent variable. Following Schwartz and Akaike information criteria, we choose the optimal number of lags and we correct the coefficient variance/covariance matrix for autocorrelation and heteroscedasticity using the Newey-West method. Hour of the day and day of the week dummy variables are also included.

4.4. Cross-Over Trading Strategies

The aim of this analysis is to test whether individual investors contrarian behavior is based on information and not to investigate the relative performance of various trading rules and strategies and propose a money-making trading strategy that maximizes profits. Therefore, we deploy a simple cross over trading strategy that generates buy and sell signals opposite to that indicated by individual investors Net Order Flow. More specifically, we sell EURUSD when the short term moving average of Net Order Flow crosses above the long term moving average of Net Order Flow and buy EURUSD when the short term moving average of Net Order Flow crosses below the long term moving average of Net Order Flow.

Each time we receive a buy (sell) signal, we take a long (short) position in EURUSD currency pair and we calculate the mean and median log return series statistics, for non-overlapping signals, for holding period from 1 hour up to 20 hours after the signal. As this study is based on an intraday analysis, we have developed three different trading cross-over strategies, using the 3 hours, the 4 hours and the 6 hours aggregation periods. All the intraday aggregation periods are cross over the daily moving average, leading to the following three cross-overs: 3 hours moving average vs daily moving average, 4 hours moving average vs daily moving average and 6 hours moving average vs daily moving average. Each of the three trading strategies is evaluated both in-sample and out-of-sample. In order to have sufficient number of signals in both samples for all holding period windows, we split the sample into two equally weighted datasets. Our results from the three different cross-over strategies are qualitative the same, thus only the results for cross-over strategy 3hours vs daily moving average are reported.

5. Empirical Results

5.1. Scheduled Announcements and Trading Behavior

5.1.1. Event Study Analysis

Tables 3, Panel A (Panel B), reports event study results for the abnormal cumulative Net Order Flow, Net Long, Net Short and Overall Unsigned Volume around negative (positive) surprise scheduled macroeconomic announcements. Event windows are constructed using 5-minute data and cumulative abnormal values are reported for different sub-periods of the event window [-60min, +60min].

The documented results in the pre-event windows are consistent with the uninformed status of the retail investors in our sample. More specifically, there is no significant abnormal reaction for Net Order Flow, Net Long and Net Short in the pre-event windows for both negative and positive surprise events (Panel A and B respectively). In the period before the announcement there is no evidence of significant reaction in trading activity.

Regarding the trading behavior at the announcement and post the announcement, our results indicate a statistically significant increase, in the overall unsigned volume consistent with the hypothesis that retail investors increase their overall trading activity after scheduled macro announcements. Results on the Net Order Flow variable at the post-announcement periods, indicate a contrarian behavior over the surprise of the announcement. More specifically, we document significant positive (negative) Net Order Flow for negative (positive) surprise events indicating that retail investors exhibit a euro buying (selling) pressure after negative (positive) surprise announcements. These results are aligned with our second hypothesis indicating a negative relation between order flow and announcement content, after the announcement.

5.1.2. Panel Regressions Analysis

Results of the panel regression analysis for Net Order Flow, Net Long, Net Short and Overall Unsigned Volume (all variables are reported in millions) around negative (positive) surprise scheduled macroeconomic announcements are reported in Table 4 Panels A and B respectively. As described on Section 4.2., five versions of panel regressions are conducted. Results are quantitatively and qualitatively the same, thus only the outcomes for the stricter panel regression model are reported[33].

As expected, results in the pre-announcement periods are supporting the idea that retail investors can be considered uninformed about the content of a macroeconomic announcement. Particularly, there is no significant reaction for Net Order Flow, Net Long and Net Short in the pre-event window.

Contrast to our first hypothesis, we do not observe any significant decrease on our overall unsigned volume variable at the pre-event window while at the announcement, our results indicate a statistically significant increase, at the 1% level, for both negative and positive surprise events. By observing the negative coefficients on Net Long and Net Short positions, we can accredit this increase in the closing of already open positions rather than the opening of new ones. The decrease in Net Long (Net Short) positions in negative (positive) surprise events could be due to the "automatic" position closing (not from the side of the trader itself) since in negative surprise events (positive surprise events), the price drop (increase) will cause loses on the already opened long (short) initiated positions which along with the high leverage level that investors can obtain in the FX market will have more severe impact on trades performance and can easily lead clients margin level to drop below 20%[34]. For negative surprise events (Panel A), the drop in both Net Long and Net Short position is statistically significant, resulting in an insignificant reaction of Net Order Flow while for positive surprise events (Panel B), only the reduction in Net Short positions is statistically significant resulting in a significant increase of Net Order Flow.

The Net Order Flow behavior in the post-announcement period, aligns with the findings of our event study and is consistent with our second hypothesis. More specifically, we document that after negative surprise events, the Net Order Flow increases significantly driven by a significant increase in Net Long positions, while after positive surprise events the Net Order Flow significantly decreases, driven by a significant increase in Net Short

[33] Panel regression analysis using robust White standard errors clustered by event with country fixed effects and seasonality controls (time of the day and day of the week), are reported.
[34] In the FX market, a broker closes its client's position when client's margin level drops below 20%.

positions. This trading activity is a sign of a contrarian behavior over the surprise of the announcement.

At the post- announcement period, overall unsigned volume is found to be positive and statistically significant only for positive surprise events. In contrast to our previous result according to which retailers exhibit a contrarian behavior over the surprise of the announcement, the insignificant reaction in the pre and post event window of overall unsigned volume could be an indication that individuals do not actually follow macroeconomic announcements. This apparent contradiction calls for further investigation.

Kaniel et al. (2012), document that at the day of the announcement, individuals' contrarian trading behavior arise basically from their return-contrarian behavior and not from the sign of the earning's surprise itself. Figure 3, presents individuals' tendency to trade based on returns with this tendency being more pronounced for negative surprise events for which the surprise's impact on returns is more instantaneous[35]. Based on Kaniel et al. (2012) notion we rerun our panel regression analysis, controlling for the effect that past returns may have on individual investors order flow. Table 5 Panel A (Panel B), reports the results after including lagged return controls. We can see that in the pre-announcement period and at the announcement period results remain the same. But after the announcement we observe that on negative surprise events the contrarian behavior of individual investors over the surprise of the announcement disappears, while for positive surprise events, we document a persistence of their news-contrarian behavior even after controlling for past returns. Summarizing panel regression results, we document that individuals trading buy and sell preferences are mostly driven by lagged return movements rather than the surprise of the announcement itself, even though there is a news-contrarian tendency in positive surprise events.

The return contrarian tendency of individual investors can be also be seen in Figure 4. In Figure 4, we are estimating the cumulative average abnormal Net Order Flow (Panel A) and the cumulative average abnormal returns (Panel B) for negative and positive surprise

[35] Existing literature examining the linkage between exchange rate returns and macroeconomic news at an intraday basis find that the main impact occurrs within 20 minutes (Ederington and Lee (1996), Andersen and Bollerslev (1998), Almeida et al. (1998), Andersen et al. (2003), Dominiquez and Panthaki (2006)). In addition, Andersen et al. (2003) provide evidence of stronger impact of bad news rather than good news.

component of FOMC monetary policy decisions. Karnaukh (2016), by using 5-minute data for four currencies, quoted against US dollar (including EUR), documents a dollar movement two days before the FOMC meeting, in anticipation of the surprise of the FOMC monetary policy decision. By observing individual investors order flow during that period, we can see that their trading behavior exhibits a contradictive anticipation of the surprise of the FOMC announcement. Documented results highlight the importance of examining the effects of returns on individual investors order flow on an intraday basis. Kaniel et al. (2008), Kaniel et al. (2012) and Menchoff et al. (2016), show the return contrarian behavior of individual investors on a daily basis, with the first two studies using stock market data and the third study also including FX rate data.

5.2. News Sentiment and Trading Behavior: A Time Series Analysis.

Returns and news sentiment impact on individual investors' behavior is tested using time series analysis where the dependent variable is Net Order Flow and lagged values of the EURUSD exchange rate and lagged value of news sentiment change, are used as independent variables. Following Sun et al. (2016), who found that lagged half-hour sentiment changes impact stock market returns, we use the rolling 30-minute lagged sentiment change to test sentiment impact on individuals' Net Order Flow in the FX market. Since we are testing the news sentiment impact on individual investors EURUSD trading behavior by using the EU and US country TRMI sentiment indices, we employ and use the rolling 30-minute relative EU to US sentiment change (as described in section 3.2.3).

Results from time series regressions using the rolling 30-minute lagged sentiment change of the difference between EU and US are reported in Table 6. Model 1 presents the results including the rolling 30-minute lagged sentiment change and twelve lags of the 5-minute lagged EURUSD exchange rate return (ΔR_{t-i} where i = 1, 2, …., 12). Model 2, includes the first 5-minute lagged EURUSD exchange rate return, ΔR_{t-1} along with the cumulative $\Delta R_{t-2,\, t-12}$ lag return. Model 3 and Model 4, in addition to the predetermined independent variables, also consider the macro news' dummy variables which capture the macroeconomic announcements' impact. In all models, lags of our dependent variable[36] and hour of the day and day of the week dummy variables are included.

[36] Determined by Akaike's and Schwarz's Bayesian information criteria.

We observe that in Models 1 and 2, the rolling-30-minute lagged sentiment change is found to be positive and statistically significant at the 1% level. The statistically significant finding confirms our fourth hypothesis of a significant link between sentiment and retail investors order flow. Since we are using EU to US relative sentiment change, a positive coefficient indicates that an increase in EU to US relative sentiment change, leads individuals to exhibit a euro buying pressure[37]. More precisely, a one standard deviation increase on our news sentiment measure leads individuals to increase their euro buying by €23,306.4 (29.133*0.0008 = 0.0233064 millions) within a 5-minute interval[38]. In both models, the coefficients of lagged EURUSD exchange rate returns are found to be significantly negatively related with individuals Net Order Flow, suggesting individual investors' contrarian behavior on an intraday basis[39]. A standard deviation increases on the first 5-minute lagged return change, ΔR_{t-1}, leads individuals to decrease their euro buying, within a 5-minute interval by €667,078.2 (16.974* 0.0393=0.6670782 millions) in Model 1 and by €658,392.9 (16.753* 0.0393=0.6583929 millions) in Model 2. This result concurs Menkhoff et al. (2016) finding, according to which individual investors are return contrarians on a daily basis. Results remain qualitatively the same even after controlling for the impact that macro variables can cause to Net Order Flow[40] (Models 3 and 4).

5.3. Cross-Over Trading Strategies Results

Table 6, Panel A (Panel B), presents the in-sample (out-of-sample) mean and median log returns to a strategy that sells EURUSD when the short term (3 hours) moving average of Net Order Flow crosses above the long term (daily) moving average of Net Order Flow and buys EURUSD when the short term (3 hours) moving average of Net Order Flow crosses below the long term (daily) moving average of Net Order Flow.

It is evident that almost all holding periods infer successful trading strategies. For the in-sample analysis, the mean and median returns are presented to be positive and statistically significant for holding period greater or equal to 4 hours. The maximum mean and median

[37] Since individuals' Net Order Flow is given as we have described in section 3.1.1, in euro money terms, we interpret an increase in individuals' Net Order Flow as a euro buying pressure and a decrease as a euro selling pressure.
[38] Results remain identical after controlling for the level of sentiment.
[39] Results are qualitatively the same even after using Menkhoff et al. (2016) standardized measure for Net Order Flow.
[40] Stambaugh et al. (2012), show that the impact of sentiment is vigorous after controlling for macro variables.

return combination for long and short position is achieved with a 20-hour holding period. Over this period, we receive 31 long signals and 47 short signals with average mean return for long signals of 0.403% and for short signals an average mean returns of 0.240%. The corresponding median return is 0.390% and 0.108% respectively. In all cases, returns find to be statistically significant at 1% level. As in the in-sample analysis, out-of-sample analysis results are qualitatively the same.

The fact that the trading strategy generates positive results both in-sample and out-of-sample, shows that collectively individuals investors order flow has no information about future FX returns but is helping in the stabilization of the market through their liquidity provision role.

6. Conclusions

In this research project we aim to investigate effect of scheduled macro news announcements and news sentiment on retail investors' order flow in FX markets. We achieve that, by using a proprietary intraday dataset of aggregate long and short positions of retail investors in EURUSD for the period July 2014 to April 2016, along with a new intraday news sentiment provided by TRMI and scheduled macro news announcements in both the US and Euro area.

Even if there is an extensive literature trying to link interdealer market order flow with FX pricing and substantial literature trying to link investor sentiment with asset prices fluctuations, to the extent of our knowledge, there is no other work that examines the effect of macro scheduled announcements and news sentiment on retail investors' order flow in FX markets.

It's crucial to identify retail investors' behavior, separated from other trader types (institutions, corporations, interdealer e.t.c), since retail investors are likely to differ in the quantity and quality of private information they possess as well as in their trading motives and trading strategies. Understanding how individuals form their trading decisions and what influence their trading strategies, policy makers, can help them to assess and improve if needed the efficacy of investors' regulatory protections.

First, we provide evidence consistent with the uninformed status of retail investors; second, we show significant reaction of retail investors around macro news announcements; and third, we find that returns and news sentiment affect their trading activity on an intraday basis. More specifically, there is no significant abnormal reaction for Net Order Flow, Net Long and Net Short in the pre-event windows for both negative and positive surprise events. Results on the Net Order Flow variable at the post-announcement periods, indicate a contrarian behavior over the surprise of the announcement. Particularly, we document significant positive (negative) Net Order Flow for negative (positive) surprise events indicating that retail investors exhibit a euro buying (selling) pressure after negative (positive) surprise announcements. Like Kaniel et al. (2012) we show that, their contrarian behavior over the surprise of the announcement is mostly driven by returns movements rather than the surprise of the announcement itself, even though there is a news-contrarian tendency in positive surprise events. Furthermore, by testing the predicting power of news sentiment on retails investor order flow we find evidence that the rolling 30-minute lagged sentiment change, strongly predicts their trading activity. Inclusion of lagged EURUSD exchange rate returns in our time series model, where the dependent variable is retail investors Net Order Flow, shows retail investors contrarian trading behavior on an intraday basis. This result is consistent with Menkhoff et al. (2016) finding, that individual investors are return contrarians on a daily basis.

In an effort to examine if collectively individuals order flow has information about future returns, we deploy a simple cross over trading strategy, that generates buy and sell signals opposite to that indicated by individual investors Net Order Flow. By estimating the mean and median returns for different holding periods, the strategy yields statistically significant returns for almost all tested holding periods for both, in-sample and out-of-sample analysis, indicating that individuals trading is not based on information. Observed results indirectly suggest that retail investors contrarian behavior add value to the market by providing liquidity to informed investors.

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Figure 1: Time of the day seasonal pattern.

Figure 1 shows the time of the day seasonal pattern.

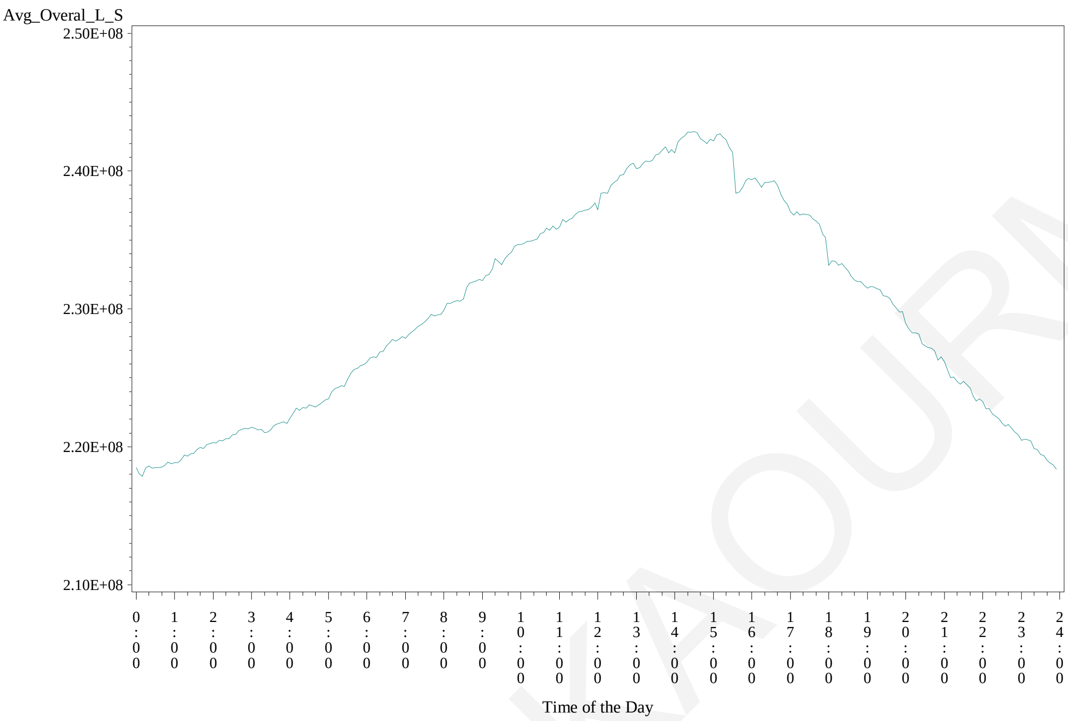


Figure 2: Day of the week seasonal pattern.

Figure 2 shows the day of the week seasonal pattern.

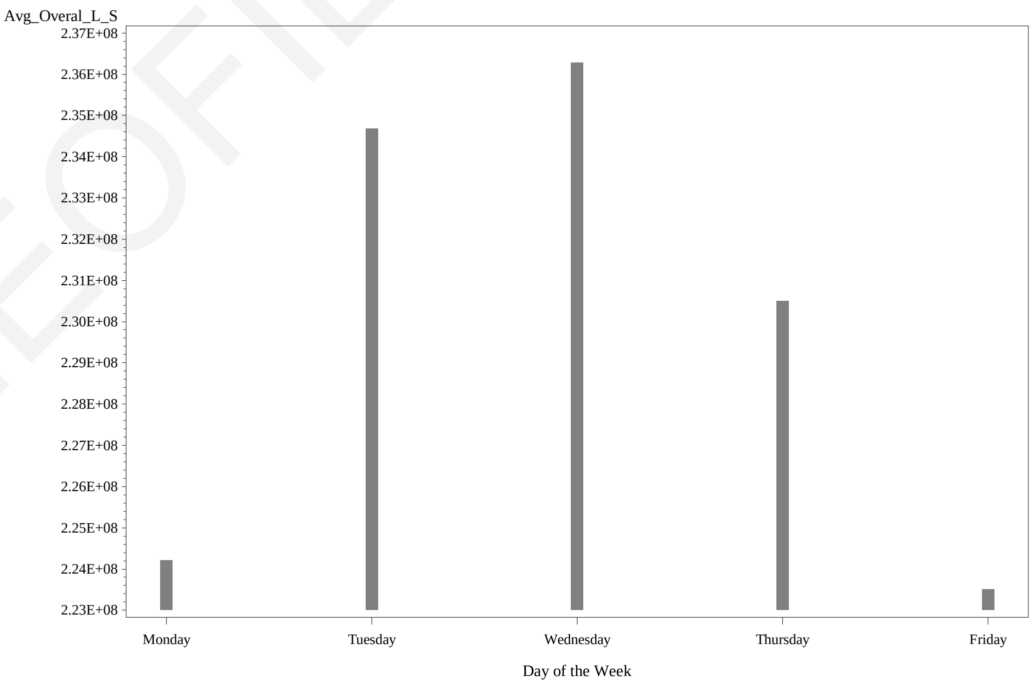
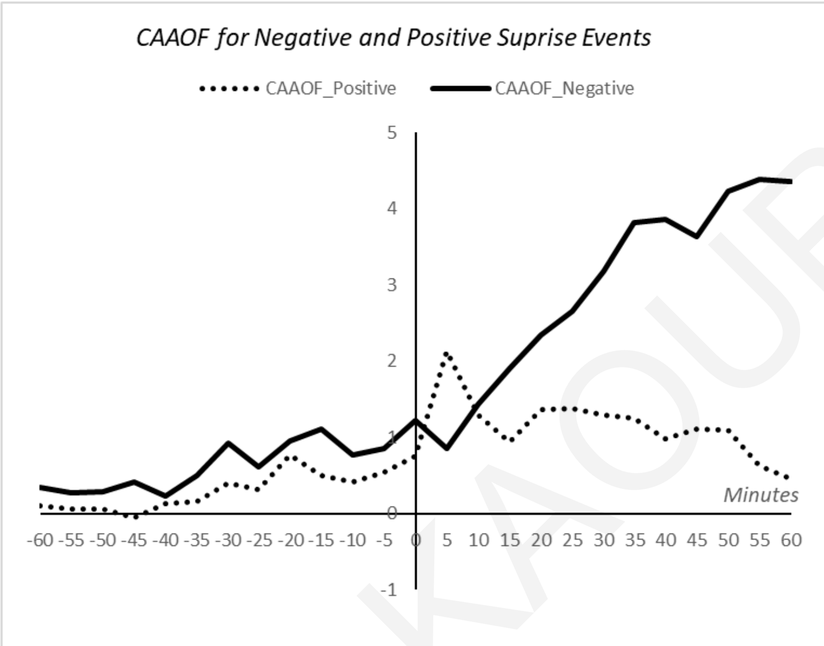


Figure 3: Cumulative average abnormal Net Order Flow (CAAOF) and cumulative average abnormal returns for negative and positive surprise events.

We drop from our sample overlapping events (from event and estimation window) and end up with 162 negative and 168 positive surprise events. Panel A (Panel B) shows the CAAOF (CAARs) for negative (solid line) and positive (dushed line) surprise events

A



B

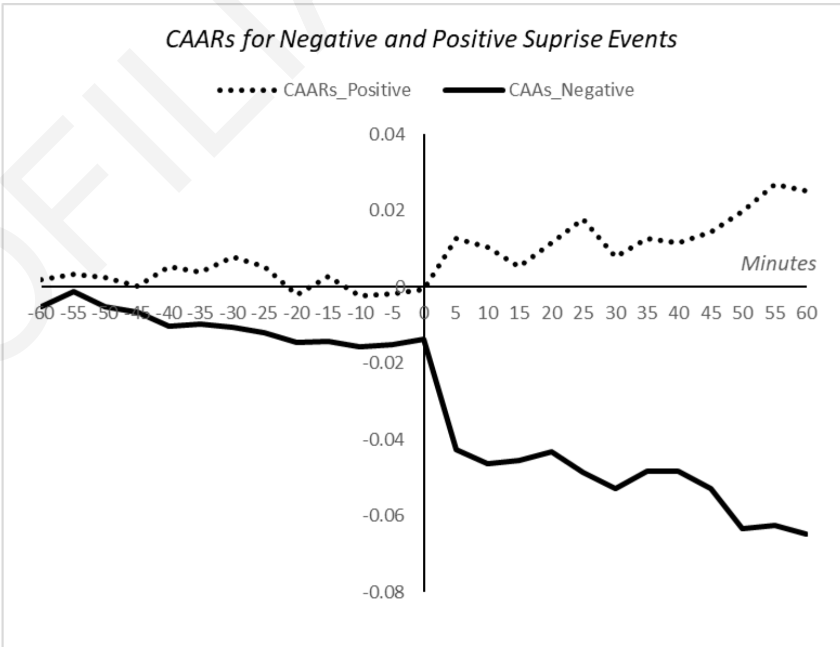
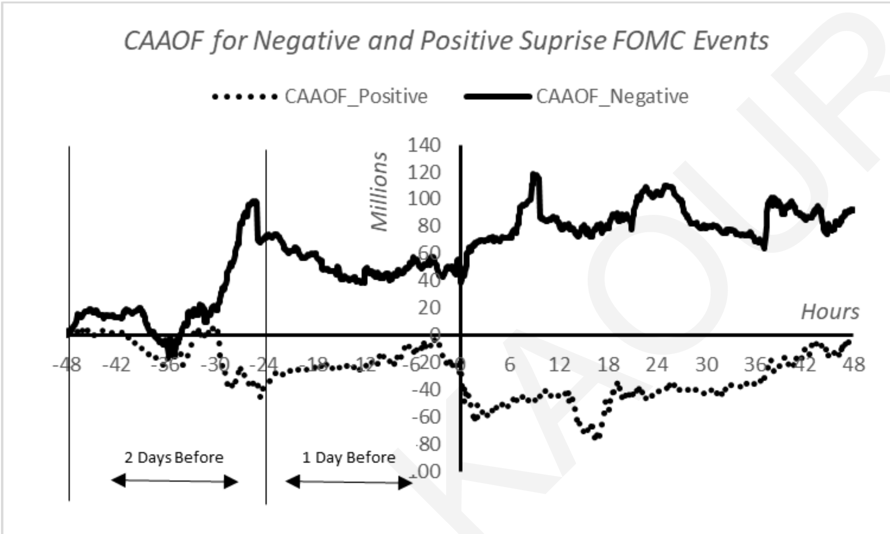


Figure 4: Cumulative average abnormal Net Order Flow (CAAOF) and cumulative average abnormal returns (CAARs) for negative and positive surprise component of FOMC monetary policy decisions.

In our sample period we only have 2 negative and 3 positive suprices for FOMC decisions. In order to identify the surprise component of monetary policy decisions we are using the standard methodology employ in Kuttner (2001), (see detailed description on Section 3.1.2.). An abnormal value is defined as the actual value of the variable of interest over the event window, minus the expected value over the event window. We use the constant mean method, for estimating the expected value of the variable under examination. The event window is defined as the period two days before the event until two days after the event and as estimation window, we define the period 31 days before the event to 3 days before the event. Panel A (Panel B) shows the CAAOF (CAARs) for negative (solid line) and positive (dushed line) surprise events.

A



B

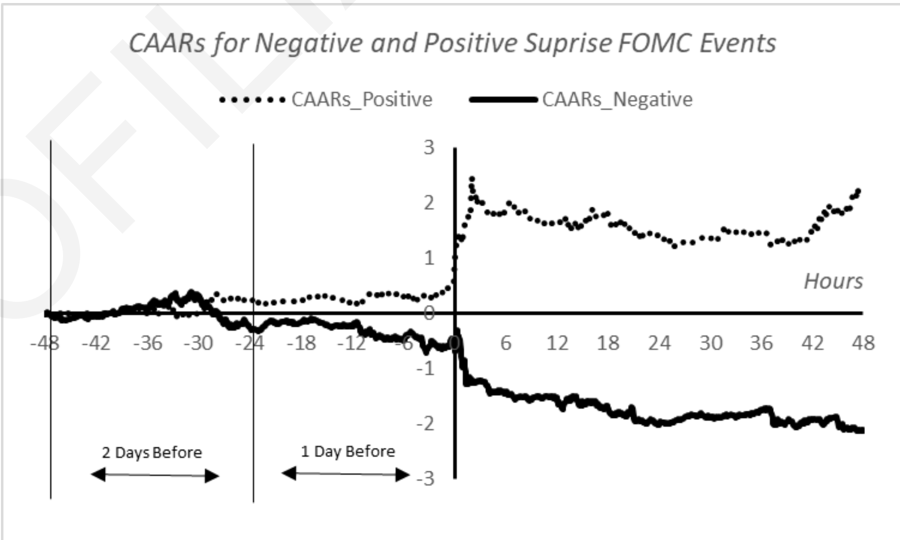


Table 1: Summary Statistics of scheduled macro announcements.

Country | Frequency	Announcements	Classifications	Sign
United States			
Monthly			
	Capacity Utilization	Industry Sector	+
	Construction Spending	Industry Sector	+
	Consumer Confidence Index	Surveys & Cyclical	+
	Consumer Credit	Government Sector	+
	Consumer Price Index - CPI	Prices	+
	Durable Goods	Industry Sector	+
	Factory Orders	Industry Sector	+
	Gross Domestic Product - GDP*	National Account	+
	Government Budget Deficit	Government Sector	+
	Housing Starts	Industry Sector	+
	ISM Index	Surveys & Cyclical	+
	Index of leading indicators	Surveys & Cyclical	+
	Industrial Production	Industry Sector	+
	New Home Sales	Industry Sector	+
	Non - Farm Payrolls	Labour Market	+
	Personal Income	National Account	+
	Producer Price Index - PPI	Prices	+
	Retail Sales	Consumer Sector	+
	Trade Balance	External Sector	+
	Unemployment Rate	Labour Market	-
	Vechicle Sales	Consumer Sector	+
	Whole Sales	Consumer Sector	-
Every Six Week	Federal Fund Futures	Other	+
Weekly	Initial Unemployment Claims	Labour Market	-
Eurozone			
Monthly			
	Consumer Confidence Index	Surveys & Cyclical	+
	Euribor Futures	Other	+
	Eurostat Trade	External Sector	+
	Gross Domestic Product - GDP	National Account	+
	Industrial Production	Industry Sector	+
	M3 - Money Supply	Government Sector	+
	PMI Index	Surveys & Cyclical	+
	Producer Price Index - PPI	Prices	+
	Retail Sales	Consumer Sector	+
	Unemployment Rate	Labour Market	-
Every Six Week	Euribor Futures	Other	+

* There are three types of GDP announcements, namely, GDP advance, GDP preliminary and GDP final. Each type is announced at a quarterly basis. However, the overall frequency of announcements is at a monthly basis, since each type of GDP is announced at a different month of a quarter.

Table 2: Summary Statistics of Long initiated positions, Short initiated positions, Net Long, Net Short, Net Order Flow, Changes of Overall Unsigned Volume, the 30-minute, EU vs US sentient change and EURUSD Return.

We use Net Order Flow , Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Net Order Flow is a signed trading volume and is calculated as the difference between the Net Long and Net Short positions, where the Net Long and Net Short positions are the changes in the long and short open interest per 5-minutes, respectively. For example, $\text{Net Long}_{i,t} = \text{Long}_{i,t} - \text{Long}_{i,t-1.}$ The sum of Net Long and Net Short positions provide a measure of overall trading volume/intensity and we denote it as Overall Unsigned Volume. ΔS_EUvsUS, refers to the 30-minute EU vs US TRMI sentiment change (see detailed description on Section 3.2.3.). The exchange rate return at time t is measured as the percentage of the difference in the log of exchange rate prices between time t and t-1.

Variable	Mean	Median	Minimum	Maximum	Std Dev
Long Initiated Positions	102,343,005	99,350,120	24,355,180	316,000,000	42,535,073
Short Initiated Positions	125,373,052	120,269,500	26,352,690	363,000,000	48,419,837
Net_Long Initiated Positions	-1,254	0	-98,000,000	58,000,000	1,995,204
Net_Short Initiated Positions	3,188	0	-69,000,000	49,000,000	2,178,731
Net_Order_Flow	-4,418	0	-113,000,000	102,000,000	2,988,562
Overall_Unsign_Volume	1,855,923	1,000,000	0	145,000,000	3,039,106
ΔS_EUvsUS	0.0000	0.0000	-0.0445	0.0428	0.0008
Return	-0.0001	0.0000	-1.5089	1.6599	0.0393

Table 3: Event study results on the behavior of retail investors around macroeconomic news announcements.

This table presents event study results of how retail investors behave around macroeconomic news announcements. We use Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Using the announcements' surprise component, we classified announcements into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. We then measure cumulative abnormal values over different sub-periods of the event window [-60min, +60min], capturing retail investors behavior in period before, during and after the announcement. Panel A (Panel B) reports, cumulative abnormal values, for negative (positive) surprise events along with the level of their statistical significance (SS). ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

Panel A: Event study results for Negative Suprise Events

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Relative Time	Median	SS	Median	SS	Median	SS	Median	SS
[-60,-20]	251560.2		79111.6		-186778.2		78360.8	
[-60,-15]	465265.0		180034.0		-433647.0		358904.0	
[-15,-5]	-331024.6		226138.2		74709.4		-52124.4	
[-10,-5]	-62222.6		198804.8		97867.2		-308633.4	
[0,+5]	80000.0		35747.2		-139885.6		963484.8	***
[+10,+15]	363674.6	**	456251.0	***	-47347.0		480000.0	***
[+10,+20]	980478.6	**	703004.9	***	-110562.0		760123.6	***
[+20,+60]	773757.6	*	384359.6		-648916.0	**	1586597.6	*
[+25,+60]	1473202.4	*	272979.2		-989089.6	***	1138606.0	

Panel B: Event study results for Positive Suprise Events

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Relative Time	Median	SS	Median	SS	Median	SS	Median	SS
[-60,-20]	-531903.6		-290669.6		41031.2		-128668.4	
[-60,-15]	-713264.0		-299920.0		92534.0		620000.0	
[-15,-5]	-377144.8		-43024.8		220410.4		-500000.0	
[-10,-5]	-160000.0		113043.5		203506.0		-539820.4	*
[0,+5]	493844.8	**	400000.0		-368779.8	***	894998.6	***
[+10,+15]	-516778.6	**	-29328.4		574788.6	***	414044.2	**
[+10,+20]	-200000.0		138674.0		662894.4	**	1080000.0	***
[+20,+60]	-916656.6		-189705.2		538354.4		2437173.8	***
[+25,+60]	-754403.0		-218852.8		543526.0		1254996.8	**

Table 4: Panel Regressions of individual investors' behavior around macroeconomic announcements.

This table presents panel regression results, where the dependent variable is the behavior of individual investors (in millions) and as independent variables the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 162)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.117		0.024		-0.106		0.125	
	(0.335)		(0.764)		(0.159)		(0.310)	
Relative time [-60,-15]		0.121		0.021		-0.113		0.100
		(0.299)		(0.776)		(0.131)		(0.348)
Relative time [-15,-5]	-0.019		-0.093		-0.078		-0.030	
	(0.905)		(0.316)		(0.528)		(0.823)	
Relative time [-10,-5]		-0.105		-0.137		-0.030		0.014
		(0.576)		(0.250)		(0.834)		(0.934)
Relative time [0,+5]	0.003	0.003	-0.676**	-0.676**	-0.698**	-0.698**	1.597***	1.597***
	(0.992)	(0.992)	(0.041)	(0.041)	(0.028)	(0.028)	(0.003)	(0.003)
Relative time [+10,+15]		0.540**		0.369**		-0.192		0.324
		(0.048)		(0.020)		(0.317)		(0.149)
Relative time [+10, +20]	0.484**		0.362**		-0.155		0.217	
	(0.039)		(0.011)		(0.321)		(0.233)	
Relative time [+20,+60]		0.242**		0.047		-0.233***		-0.004
		(0.047)		(0.527)		(0.009)		(0.970)
Relative time [+25,+60]	0.226*		0.009		-0.252***		-0.004	
	(0.064)		(0.901)		(0.007)		(0.967)	
Constant	-0.320***	-0.320***	-0.004	-0.004	0.367***	0.367***	0.160	0.160
	(0.008)	(0.008)	(0.954)	(0.951)	(0.000)	(0.000)	(0.180)	(0.180)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,518	7,518	7,544	7,544	7,558	7,558	7,439	7,439
R-squared (within)	0.0155	0.0156	0.0081	0.0078	0.0064	0.0064	0.1413	0.1414
Panel B: Positive Events (# 168)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.051		-0.024		-0.084		-0.024	
	(0.661)		(0.769)		(0.308)		(0.753)	
Relative time [-60,-15]		0.011		-0.056		-0.078		-0.020
		(0.922)		(0.471)		(0.320)		(0.792)
Relative time [-15,-5]	-0.141		-0.219**		-0.093		-0.132	
	(0.372)		(0.044)		(0.431)		(0.320)	
Relative time [-10,-5]		-0.033		-0.152		-0.129		-0.201
		(0.869)		(0.231)		(0.377)		(0.158)
Relative time [0,+5]	0.818**	0.818**	-0.110	-0.110	-0.949***	-0.949***	1.429***	1.429***
	(0.015)	(0.015)	(0.623)	(0.622)	(0.001)	(0.001)	(0.000)	(0.000)
Relative time [+10,+15]		-0.760***		-0.139		0.587***		0.280
		(0.004)		(0.460)		(0.001)		(0.165)
Relative time [+10, +20]	-0.390*		0.058		0.438***		0.421***	
	(0.084)		(0.678)		(0.007)		(0.009)	
Relative time [+20,+60]		-0.050		-0.050		0.012		0.077
		(0.660)		(0.537)		(0.886)		(0.419)
Relative time [+25,+60]	-0.098		-0.112		-0.003		-0.002	
	(0.383)		(0.170)		(0.969)		(0.986)	
Constant	-0.122	-0.121	0.091	0.091	0.258*	0.258*	0.234*	0.234*
	(0.438)	(0.439)	(0.308)	(0.308)	(0.092)	(0.092)	(0.094)	(0.094)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,660	7,660	7,712	7,712	7,641	7,641	7,525	7,525
R-squared (within)	0.0380	0.0388	0.0165	0.0162	0.0173	0.0177	0.1819	0.1814

Table 5: Panel Regressions of individual investors' behavior around macroeconomic announcements, controlling for returns.

This table is similar to Table 4 but with returns as additional control variables. It presents panel regression results, where the dependent variable is the behavior of individual investors (in millions) and as independent variables the dummy variables capturing the relative time of interest, lags of our dependent variable as well as lags for returns. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistic al significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 162)

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.077		-0.000		-0.088		0.125	
	(0.504)		(0.997)		(0.218)		(0.310)	
Relative time [-60,-15]		0.080		-0.006		-0.097		0.100
		(0.465)		(0.936)		(0.174)		(0.348)
Relative time [-15,-5]	-0.064		-0.130		-0.073		-0.030	
	(0.665)		(0.151)		(0.538)		(0.823)	
Relative time [-10,-5]		-0.149		-0.169		-0.024		0.014
		(0.387)		(0.149)		(0.860)		(0.934)
Relative time [0,+5]	-0.025	-0.025	-0.677**	-0.677**	-0.681**	-0.681**	1.597***	1.597***
	(0.931)	(0.931)	(0.044)	(0.044)	(0.035)	(0.035)	(0.003)	(0.003)
Relative time [+10,+15]		0.183		0.180		-0.022		0.324
		(0.483)		(0.235)		(0.905)		(0.149)
Relative time [+10, +20]	0.187		0.191		-0.016		0.217	
	(0.386)		(0.157)		(0.913)		(0.233)	
Relative time [+20,+60]		0.156		-0.016		-0.187**		-0.004
		(0.131)		(0.825)		(0.017)		(0.970)
Relative time [+25,+60]	0.151		-0.045		-0.211***		-0.004	
	(0.146)		(0.535)		(0.010)		(0.967)	
Constant	-0.314***	-0.314***	0.006	0.006	0.365***	0.365***	0.160	0.160
	(0.005)	(0.005)	(0.921)	(0.923)	(0.000)	(0.000)	(0.180)	(0.180)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Lag Returns	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,502	7,502	7,490	7,490	7,502	7,502	7,439	7,439
R-squared (within)	0.0797	0.0798	0.0426	0.0424	0.0367	0.0366	0.1413	0.1414

Panel B: Positive Events (# 168)

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.089		-0.007		-0.110		-0.026	
	(0.401)		(0.924)		(0.165)		(0.737)	
Relative time [-60,-15]		0.036		-0.047		-0.098		-0.022
		(0.723)		(0.529)		(0.195)		(0.773)
Relative time [-15,-5]	-0.189		-0.260**		-0.080		-0.137	
	(0.218)		(0.018)		(0.500)		(0.300)	
Relative time [-10,-5]		-0.058		-0.185		-0.126		-0.206
		(0.745)		(0.129)		(0.374)		(0.145)
Relative time [0,+5]	0.774**	0.774**	-0.131	-0.132	-0.938***	-0.938***	1.436***	1.436***
	(0.019)	(0.019)	(0.559)	(0.558)	(0.001)	(0.001)	(0.000)	(0.000)
Relative time [+10,+15]		-0.534**		-0.051		0.441***		0.279
		(0.025)		(0.762)		(0.009)		(0.170)
Relative time [+10, +20]	-0.274		0.125		0.351**		0.422***	
	(0.196)		(0.342)		(0.022)		(0.009)	
Relative time [+20,+60]		-0.006		-0.013		-0.013		0.068
		(0.959)		(0.867)		(0.874)		(0.471)
Relative time [+25,+60]	-0.036		-0.073		-0.035		-0.012	
	(0.742)		(0.356)		(0.661)		(0.903)	
Constant	-0.210	-0.210	0.061	0.062	0.323*	0.323*	0.238*	0.238*
	(0.216)	(0.216)	(0.416)	(0.416)	(0.064)	(0.064)	(0.086)	(0.086)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Lag Returns	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,660	7,660	7,673	7,673	7,641	7,641	7,525	7,525
R-squared (within)	0.1149	0.1151	0.061	0.0604	0.063	0.0631	0.1832	0.1827

Table 6: Time Series analysis for the impact of sentiment on individual investors' behavior.

This table presents time series regressions' results, where the dependent variable is the behavior of individual investors (as captured by individuals' Net Order Flow) and as independent variables the rolling 30-minute lagged sentiment change of the difference between EU and US sentiment. Model 1 includes the rolling 30-minute lagged sentiment change and the 12, 5-minute lagged EURUSD exchange rate returns. Model 3 includes the rolling 30-minute lagged sentiment change and the exchange rate return over the prior 5 minute, ΔR_{t-1}, and over the prior 12 minutes, $\Delta R_{t-2,\ t-12}$. Model 2 and Model 4, in addition to the predetermined independent variables in Model 1 and Model 3 respectively, it also considers the macro news' dummy variables which capture the macroeconomic announcements' impact. Dummy variables created to capture the impact for the time period [-60min, +60min]. Time series' regression coefficients and p-values (in parenthesis) are reported. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

Independent Variables	Model 1	Model 2	Model 3	Model 4
Lagged-Rolling 30-min	29.133***	30.506***	29.168***	30.542***
Sentiment Change	(0.008)	(0.006)	(0.008)	(0.006)
Lagged Returns				
ΔR_{t-1}	-16.974***		-16.978***	
	(0.000)		(0.000)	
ΔR_{t-2}	-9.121***		-9.123***	
	(0.000)		(0.000)	
ΔR_{t-3}	-5.105***		-5.104***	
	(0.000)		(0.000)	
ΔR_{t-4}	-2.988***		-2.985***	
	(0.000)		(0.000)	
ΔR_{t-5}	-2.485***		-2.482***	
	(0.000)		(0.000)	
ΔR_{t-6}	-1.425***		-1.425***	
	(0.000)		(0.000)	
ΔR_{t-7}	-1.159***		-1.166***	
	(0.001)		(0.000)	
ΔR_{t-8}	-0.554*		-0.555*	
	(0.073)		(0.073)	
ΔR_{t-9}	-0.641**		-0.643**	
	(0.046)		(0.045)	
ΔR_{t-10}	-0.622**		-0.629**	
	(0.037)		(0.034)	
ΔR_{t-11}	-0.617*		-0.622*	
	(0.073)		(0.071)	
ΔR_{t-12}	-0.665**		-0.668**	
	(0.030)		(0.029)	
ΔR_{t-1}		-16.753***		-16.748***
		(0.000)		(0.000)
$\Delta R_{t-2,\ t-12}$		-1.821***		-1.819***
		(0.000)		(0.000)
Constant	-0.042	-0.030	-0.046	-0.032
	(0.153)	(0.298)	(0.114)	(0.262)
Lags of Dependent Variable	Yes	Yes	Yes	Yes
Macro News	No	No	Yes	Yes
Hour_of_the_Day	Yes	Yes	Yes	Yes
Day_of_the_Week	Yes	Yes	Yes	Yes
Observations	126,052	126,700	126,052	126,700
Adjusted R-squared	0.0752	0.0574	0.0755	0.0578

Table 7: Mean and Median return of the in-sample and out-of-sample trading strategy.

This table presents mean and median returns from a simple cross over trading strategy that generates buy and sell signals opposite to that indicated by individual investors Net Order Flow. It generates sell signals of EURUSD when the short term (3 hours) moving average of Net Order Flow crosses above the long term (daily) moving average of Net Order Flow and buy signals of EURUSD when the short term (3 hours) moving average of Net Order Flow crosses below the long term (daily) moving average of Net Order Flow. We then calculate the mean and median log returns on EURUSD for holding period 1 to 20 hours for non-overlapping signals. Panel A (Panel B) reports mean and median results along with the level of their statistical significance (SS), for the in-sample (out-of-sample) analysis. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

		Panel A: Cross- Over Strategy - In-Sample					Panel B: Cross- Over Strategy - Out-of-Sample				
Holding period	Strategy signal	N	Mean	SS	Median	SS	N	Mean	SS	Median	SS
1 hour	long	204	-0.017		-0.007		207	0.002		-0.010	
1 hour	short	211	0.007		-0.008		213	0.021	**	0.011	*
2 hours	long	190	0.003		-0.001		187	0.018		0.011	
2 hours	short	196	0.008		0.002		198	0.026	**	0.012	
3 hours	long	170	0.023		0.013		169	0.032	**	0.015	**
3 hours	short	177	0.029		0.017		177	0.042	***	0.023	**
4 hours	long	152	0.054	**	0.033	***	152	0.049	***	0.044	***
4 hours	short	156	0.033	*	0.018		156	0.065	***	0.044	***
5 hours	long	139	0.066	**	0.039	***	141	0.052	***	0.048	***
5 hours	short	139	0.049	**	0.022	**	144	0.088	***	0.055	***
6 hours	long	129	0.089	***	0.062	***	129	0.071	***	0.062	***
6 hours	short	131	0.073	**	0.047	***	133	0.109	***	0.091	***
7 hours	long	121	0.074	**	0.069	***	112	0.089	***	0.095	***
7 hours	short	124	0.089	***	0.050	***	122	0.107	***	0.070	***
8 hours	long	112	0.112	***	0.093	***	100	0.122	***	0.111	***
8 hours	short	115	0.099	***	0.060	***	114	0.095	***	0.084	***
9 hours	long	103	0.121	***	0.114	***	98	0.128	***	0.112	***
9 hours	short	111	0.095	**	0.046	***	102	0.110	***	0.095	***
10 hours	long	94	0.123	***	0.096	***	87	0.167	***	0.181	***
10 hours	short	101	0.064		0.050	**	96	0.140	***	0.115	***
11 hours	long	84	0.170	***	0.140	***	82	0.176	***	0.178	***
11 hours	short	94	0.088	*	0.058	**	89	0.146	***	0.122	***
12 hours	long	72	0.230	***	0.188	***	75	0.213	***	0.211	***
12 hours	short	85	0.100	**	0.069	**	77	0.192	***	0.156	***
13 hours	long	63	0.250	***	0.193	***	68	0.190	***	0.270	***
13 hours	short	77	0.149	***	0.072	***	73	0.229	***	0.181	***
14 hours	long	60	0.217	***	0.135	***	61	0.228	***	0.275	***
14 hours	short	69	0.207	***	0.138	***	65	0.286	***	0.270	***
15 hours	long	50	0.300	***	0.184	***	56	0.297	***	0.307	***
15 hours	short	66	0.198	***	0.126	***	61	0.311	***	0.249	***
16 hours	long	42	0.383	***	0.227	***	52	0.301	***	0.366	***
16 hours	short	64	0.177	***	0.169	***	59	0.292	***	0.248	***
17 hours	long	41	0.405	***	0.255	***	50	0.308	***	0.333	***
17 hours	short	58	0.210	***	0.098	***	56	0.256	***	0.219	***
18 hours	long	37	0.373	***	0.289	***	46	0.316	***	0.359	***
18 hours	short	57	0.195	***	0.093	***	47	0.273	***	0.240	***
19 hours	long	35	0.361	***	0.277	***	37	0.336	***	0.374	***
19 hours	short	52	0.221	***	0.122	***	37	0.301	***	0.284	***
20 hours	long	31	0.403	***	0.390	***	31	0.348	***	0.414	***
20 hours	short	47	0.240	***	0.108	***	36	0.295	***	0.295	***

Appendix

- Table A1: Panel regressions results on the behavior of retail investors around macroeconomic news announcements by removing holidays.
- Table A2: Panel regressions results on the behavior of retail investors around macroeconomic news announcements by using different estimation windows.
  - Table A2.1: Estimation period equals to 4 hours before the event to 1 hour before the event.
  - Table A2.2: Estimation period equals to 6 hours before the event to 1 hour before the event.

- Table A3: Panel regressions results on the behavior of retail investors around macroeconomic news announcements by using the Barber and Odean (2008) abnormal volume's standardization method.
  - Table A3.1: Standardizing net order flow measure, $\frac{V-\bar{V}}{\sigma}$, by subtracting the rolling 1-week-mean value of net order flow and dividing by the 1-week-standard deviation of net order flow.
  - Table A3.2: Standardizing net order flow measure, $\frac{V-\bar{V}}{\sigma}$, by subtracting the rolling 1-month-mean value of net order flow and dividing by the 1-month-standard deviation of net order flow.

- Table A4: Panel regressions results on the behavior of retail investors around macroeconomic news announcements by using Menkhoff et al. (2016), standardization method.
  - Table A4.1: Standardizing net order flow measure, $\frac{V}{\sigma}$, by dividing with the 1-week-standard deviation of net order flow.
  - Table A4.2: Standardizing net order flow measure, $\frac{V}{\sigma}$, by dividing with the 1-month-standard deviation of net order flow.
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- Table A5: Panel regressions results on the behavior of retail investors around macroeconomic news announcements for both positive and negative surprise events.

- Table A6: Time Series analysis for the impact of sentiment on individual investors' behavior by using a different EU to US relative TRMI sentiment measure.

- Table A7: Time Series analysis for the impact of sentiment on individual investors' behavior by using a Net Order Flow standardization measure.
  - Table A7.1: Standardizing net order flow measure, $\frac{V}{\sigma}$, by dividing net order flow by its 1-week-standard deviation.
  - Table A7.2: Standardizing net order flow measure, $\frac{V}{\sigma}$, by dividing net order flow by its 1-month-standard deviation.

- Table A8: Trading Strategy results when using different short term moving average of Net Order Flow.
  - Table A8.1: Trading Strategy results when using the 4 hours for short term moving average of Net Order Flow.
  - Table A8.2: Trading Strategy results when using the 6 hours for short term moving average of Net Order Flow.

Table A1: Panel Regressions of individual investors' behavior around macroeconomic announcements by removing holidays.

This table is similar to Table 4 in the main text but it reports results after removing holidays. Table A1 presents panel regression results, where the dependent variable is the behavior of individual investors and as independent variables the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 162)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.115		0.014		-0.112		0.147	
	(0.366)		(0.864)		(0.150)		(0.252)	
Relative time [-60,-15]		0.115		0.011		-0.116		0.118
		(0.346)		(0.893)		(0.132)		(0.290)
Relative time [-15,-5]	-0.061		-0.122		-0.065		-0.062	
	(0.704)		(0.201)		(0.610)		(0.647)	
Relative time [-10,-5]		-0.148		-0.171		-0.021		-0.019
		(0.439)		(0.163)		(0.888)		(0.906)
Relative time [0,+5]	-0.025	-0.025	-0.717**	-0.717**	-0.710**	-0.710**	1.642***	1.641***
	(0.931)	(0.931)	(0.038)	(0.038)	(0.032)	(0.032)	(0.004)	(0.004)
Relative time [+10,+15]		0.564**		0.391**		-0.190		0.369
		(0.047)		(0.017)		(0.344)		(0.117)
Relative time [+10, +20]	0.509**		0.376**		-0.165		0.251	
	(0.037)		(0.011)		(0.314)		(0.185)	
Relative time [+20,+60]		0.238*		0.035		-0.241***		0.015
		(0.062)		(0.648)		(0.010)		(0.886)
Relative time [+25,+60]	0.218*		-0.004		-0.257***		0.015	
	(0.086)		(0.962)		(0.008)		(0.896)	
Constant	-0.303**	-0.304**	0.018	0.018	0.370***	0.370***	0.112	0.112
	(0.012)	(0.012)	(0.777)	(0.781)	(0.000)	(0.000)	(0.344)	(0.344)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,175	7,175	7,201	7,201	7,215	7,215	7,096	7,096
R-squared (within)	0.0152	0.0152	0.0086	0.0083	0.0064	0.0064	0.1406	0.1407
Panel B: Positive Events (# 168)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.074		-0.017		-0.102		-0.009	
	(0.521)		(0.840)		(0.213)		(0.912)	
Relative time [-60,-15]		0.025		-0.050		-0.087		-0.009
		(0.819)		(0.531)		(0.263)		(0.910)
Relative time [-15,-5]	-0.151		-0.225**		-0.088		-0.147	
	(0.341)		(0.039)		(0.460)		(0.273)	
Relative time [-10,-5]		-0.013		-0.161		-0.156		-0.210
		(0.949)		(0.196)		(0.291)		(0.147)
Relative time [0,+5]	0.833**	0.833**	-0.123	-0.123	-0.978***	-0.978***	1.459***	1.459***
	(0.015)	(0.015)	(0.592)	(0.591)	(0.001)	(0.001)	(0.000)	(0.000)
Relative time [+10,+15]		-0.752***		-0.138		0.581***		0.297
		(0.005)		(0.472)		(0.001)		(0.149)
Relative time [+10, +20]	-0.394*		0.060		0.444***		0.441***	
	(0.085)		(0.672)		(0.007)		(0.007)	
Relative time [+20,+60]		-0.021		-0.036		-0.006		0.074
		(0.855)		(0.659)		(0.941)		(0.440)
Relative time [+25,+60]	-0.062		-0.096		-0.027		-0.008	
	(0.576)		(0.236)		(0.739)		(0.937)	
Constant	-0.127	-0.127	0.100	0.100	0.271*	0.270*	0.212	0.213
	(0.417)	(0.419)	(0.273)	(0.273)	(0.075)	(0.075)	(0.132)	(0.132)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,513	7,513	7,565	7,565	7,494	7,494	7,378	7,378
R-squared (within)	0.0385	0.0393	0.0168	0.0164	0.0183	0.0186	0.1827	0.1822

Table A2: Panel regressions results on the behavior of retail investors around macroeconomic news announcements by using different estimation windows.

Table A2.1 : Table A2.1 is similar to Table 4 in the main text but it reports results for estimation window 4 hours before the event to 1 hour before the event. This table presents panel regression results, where the dependent variable is the behavior of individual investors and as independent variables the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 143)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.073		0.011		-0.072		0.098	
	(0.581)		(0.904)		(0.363)		(0.461)	
Relative time [-60,-15]		0.082		0.017		-0.075		0.075
		(0.516)		(0.839)		(0.333)		(0.519)
Relative time [-15,-5]	0.042		-0.022		-0.068		-0.089	
	(0.806)		(0.812)		(0.605)		(0.542)	
Relative time [-10,-5]		-0.020		-0.069		-0.050		-0.067
		(0.919)		(0.571)		(0.742)		(0.705)
Relative time [0,+5]	0.056	0.056	-0.637*	-0.637*	-0.707**	-0.707**	1.621***	1.621***
	(0.851)	(0.851)	(0.082)	(0.082)	(0.043)	(0.043)	(0.008)	(0.008)
Relative time [+10,+15]		0.601**		0.379**		-0.245		0.308
		(0.048)		(0.032)		(0.242)		(0.210)
Relative time [+10, +20]	0.543**		0.387**		-0.192		0.196	
	(0.036)		(0.013)		(0.261)		(0.327)	
Relative time [+20,+60]		0.209		0.038		-0.203**		-0.054
		(0.110)		(0.635)		(0.035)		(0.622)
Relative time [+25,+60]	0.182		-0.008		-0.217**		-0.057	
	(0.160)		(0.916)		(0.029)		(0.628)	
Constant	-0.198*	-0.198*	0.033	0.033	0.266***	0.266***	0.147	0.147
	(0.093)	(0.093)	(0.632)	(0.636)	(0.001)	(0.001)	(0.261)	(0.261)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,666	6,666	6,687	6,687	6,698	6,698	6,595	6,595
R-squared (within)	0.0166	0.0166	0.0077	0.0073	0.0063	0.0063	0.1381	0.1382
Panel B: Positive Events (# 150)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.115		0.007		-0.124		-0.029	
	(0.353)		(0.937)		(0.167)		(0.735)	
Relative time [-60,-15]		0.073		-0.020		-0.110		-0.036
		(0.533)		(0.806)		(0.200)		(0.668)
Relative time [-15,-5]	-0.084		-0.173		-0.116		-0.157	
	(0.616)		(0.128)		(0.376)		(0.273)	
Relative time [-10,-5]		0.033		-0.126		-0.184		-0.179
		(0.876)		(0.352)		(0.250)		(0.238)
Relative time [0,+5]	0.829**	0.829**	0.019	0.019	-0.832***	-0.832***	1.308***	1.308***
	(0.015)	(0.015)	(0.926)	(0.927)	(0.009)	(0.009)	(0.000)	(0.000)
Relative time [+10,+15]		-0.642**		-0.114		0.480***		0.221
		(0.015)		(0.570)		(0.003)		(0.293)
Relative time [+10, +20]	-0.317		0.027		0.329**		0.311**	
	(0.130)		(0.849)		(0.022)		(0.049)	
Relative time [+20,+60]		-0.086		-0.064		0.040		0.016
		(0.449)		(0.443)		(0.629)		(0.874)
Relative time [+25,+60]	-0.137		-0.110		0.041		-0.044	
	(0.220)		(0.198)		(0.588)		(0.689)	
Constant	-0.151	-0.151	0.075	0.075	0.273	0.272	0.318**	0.318**
	(0.416)	(0.418)	(0.404)	(0.403)	(0.119)	(0.119)	(0.034)	(0.034)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,838	6,838	6,886	6,886	6,821	6,821	6,716	6,716
R-squared (within)	0.0328	0.0333	0.0150	0.0147	0.0153	0.0157	0.1802	0.1799

Table A2.2: Table A2.2 is similar to Table 4 in the main text but it reports results for estimation window 6 hours before the event to 1 hour before the event. This table presents panel regression results, where the dependent variable is the behavior of individual investors and as independent variables the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (#128)

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.060		-0.006		-0.068		0.162	
	(0.682)		(0.956)		(0.416)		(0.266)	
Relative time [-60,-15]		0.076		0.004		-0.076		0.138
		(0.585)		(0.968)		(0.362)		(0.273)
Relative time [-15,-5]	0.010		-0.064		-0.078		-0.045	
	(0.958)		(0.532)		(0.593)		(0.782)	
Relative time [-10,-5]		-0.097		-0.139		-0.045		-0.030
		(0.649)		(0.297)		(0.787)		(0.879)
Relative time [0,+5]	0.096	0.096	-0.689*	-0.689*	-0.793**	-0.793**	1.830***	1.830***
	(0.774)	(0.774)	(0.093)	(0.093)	(0.043)	(0.043)	(0.007)	(0.007)
Relative time [+10,+15]		0.592*		0.365*		-0.255		0.367
		(0.078)		(0.063)		(0.272)		(0.182)
Relative time [+10, +20]	0.495*		0.369**		-0.164		0.230	
	(0.081)		(0.032)		(0.384)		(0.302)	
Relative time [+20,+60]		0.163		0.031		-0.156		-0.038
		(0.250)		(0.727)		(0.124)		(0.751)
Relative time [+25,+60]	0.145		-0.013		-0.177*		-0.037	
	(0.296)		(0.878)		(0.090)		(0.775)	
Constant	-0.157	-0.157	0.045	0.044	0.230***	0.229***	0.084	0.084
	(0.220)	(0.220)	(0.555)	(0.560)	(0.009)	(0.009)	(0.560)	(0.560)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,931	5,931	5,952	5,952	5,963	5,963	5,860	5,860
R-squared (within)	0.0145	0.0146	0.0074	0.0071	0.0062	0.0063	0.1355	0.1356

Panel B: Positive Events (#137)

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.124		-0.002		-0.140		0.004	
	(0.348)		(0.980)		(0.150)		(0.964)	
Relative time [-60,-15]		0.079		-0.030		-0.124		0.001
		(0.528)		(0.731)		(0.180)		(0.994)
Relative time [-15,-5]	-0.147		-0.214*		-0.098		-0.165	
	(0.402)		(0.075)		(0.479)		(0.274)	
Relative time [-10,-5]		-0.052		-0.179		-0.156		-0.230
		(0.811)		(0.204)		(0.343)		(0.144)
Relative time [0,+5]	0.808**	0.808**	-0.017	-0.017	-0.858**	-0.858**	1.330***	1.331***
	(0.027)	(0.027)	(0.939)	(0.939)	(0.011)	(0.011)	(0.001)	(0.001)
Relative time [+10,+15]		-0.619**		-0.060		0.495***		0.242
		(0.026)		(0.780)		(0.004)		(0.276)
Relative time [+10, +20]	-0.345		0.044		0.360**		0.329*	
	(0.123)		(0.769)		(0.021)		(0.050)	
Relative time [+20,+60]		-0.112		-0.095		0.043		0.038
		(0.369)		(0.294)		(0.626)		(0.730)
Relative time [+25,+60]	-0.151		-0.138		0.038		-0.020	
	(0.216)		(0.139)		(0.645)		(0.863)	
Constant	-0.191	-0.190	0.058	0.058	0.304*	0.304*	0.300*	0.300*
	(0.309)	(0.310)	(0.531)	(0.530)	(0.084)	(0.084)	(0.060)	(0.060)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,270	6,270	6,303	6,303	6,254	6,254	6,155	6,155
R-squared (within)	0.0294	0.0297	0.0146	0.0142	0.0146	0.0149	0.1731	0.1729

Table A3: Panel regressions results on the behavior of retail investors around macroeconomic news announcements by using the Barber and Odean (2008) abnormal volume's standardization method.

Table A3.1: Table A3.1 is similar to Table 4 in the main text but it reports results by using Barber and Odean (2008) standardization method. We use a standardize measure of abnormal value of the variable of interest, according to which we are subtracting the rolling 1-week-mean value of the corresponding variable and dividing by its 1-week-standard deviation, $\frac{V-\bar{V}}{\sigma}$. In this table the dependent variable is the behavior of individual investors and independent variables are the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 162)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.029		0.004		-0.051		0.074	
	(0.488)		(0.923)		(0.144)		(0.150)	
Relative time [-60,-15]		0.028		0.003		-0.052		0.060
		(0.483)		(0.947)		(0.131)		(0.173)
Relative time [-15,-5]	-0.027		-0.038		-0.025		0.012	
	(0.643)		(0.471)		(0.676)		(0.819)	
Relative time [-10,-5]		-0.051		-0.052		-0.007		0.050
		(0.473)		(0.448)		(0.919)		(0.423)
Relative time [0,+5]	-0.025	-0.025	-0.364**	-0.364**	-0.321**	-0.321**	0.615***	0.615***
	(0.799)	(0.799)	(0.028)	(0.028)	(0.043)	(0.043)	(0.000)	(0.000)
Relative time [+10,+15]		0.232**		0.205**		-0.116		0.121
		(0.018)		(0.020)		(0.210)		(0.119)
Relative time [+10, +20]	0.189**		0.206***		-0.087		0.097	
	(0.021)		(0.005)		(0.243)		(0.130)	
Relative time [+20,+60]		0.075*		0.012		-0.116**		0.039
		(0.096)		(0.761)		(0.015)		(0.324)
Relative time [+25,+60]	0.072		-0.012		-0.127**		0.037	
	(0.123)		(0.770)		(0.012)		(0.370)	
Constant	-0.136***	-0.136***	0.030	0.029	0.249***	0.249***	-0.117*	-0.117*
	(0.009)	(0.009)	(0.372)	(0.374)	(0.000)	(0.000)	(0.075)	(0.075)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,518	7,518	7,544	7,544	7,558	7,558	7,439	7,439
R-squared (within)	0.0110	0.0111	0.0078	0.0074	0.0065	0.0065	0.1158	0.1157
Panel B: Positive Events (# 168)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.020		-0.017		-0.040		0.007	
	(0.594)		(0.646)		(0.295)		(0.817)	
Relative time [-60,-15]		0.013		-0.027		-0.039		0.010
		(0.725)		(0.452)		(0.287)		(0.726)
Relative time [-15,-5]	-0.040		-0.090*		-0.047		-0.032	
	(0.469)		(0.095)		(0.396)		(0.479)	
Relative time [-10,-5]		-0.032		-0.080		-0.052		-0.066
		(0.611)		(0.221)		(0.419)		(0.168)
Relative time [0,+5]	0.252**	0.252**	-0.074	-0.074	-0.449***	-0.449***	0.579***	0.579***
	(0.042)	(0.042)	(0.550)	(0.549)	(0.000)	(0.000)	(0.000)	(0.000)
Relative time [+10,+15]		-0.208**		-0.050		0.212**		0.114*
		(0.024)		(0.556)		(0.016)		(0.083)
Relative time [+10, +20]	-0.078		0.064		0.154**		0.169***	
	(0.327)		(0.367)		(0.048)		(0.003)	
Relative time [+20,+60]		-0.004		-0.012		-0.008		0.070*
		(0.912)		(0.786)		(0.852)		(0.078)
Relative time [+25,+60]	-0.027		-0.049		-0.013		0.044	
	(0.489)		(0.252)		(0.741)		(0.294)	
Constant	-0.064	-0.064	0.041	0.041	0.154**	0.154**	-0.084*	-0.085*
	(0.237)	(0.237)	(0.386)	(0.387)	(0.038)	(0.038)	(0.056)	(0.055)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,660	7,660	7,712	7,712	7,641	7,641	7,525	7,525
R-squared (within)	0.0273	0.0280	0.0083	0.0079	0.0170	0.0173	0.1300	0.1297

Table A3.2: Table A3. is similar to Table 4 in the main text but it reports results by using Barber and Odean (2008) standardization method. We use a standardize measure of abnormal value of the variable of interest, according to which we are subtracting the rolling 1-month-mean value of the corresponding variable and dividing by its 1-month-standard deviation, $\frac{V-\bar{V}}{\sigma}$. In this table the dependent variable is the behavior of individual investors and independent variables are the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 162)

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.038		0.009		-0.056*		0.065	
	(0.336)		(0.824)		(0.097)		(0.209)	
Relative time [-60,-15]		0.039		0.010		-0.057*		0.051
		(0.308)		(0.795)		(0.087)		(0.243)
Relative time [-15,-5]	-0.016		-0.047		-0.027		0.021	
	(0.787)		(0.398)		(0.637)		(0.693)	
Relative time [-10,-5]		-0.047		-0.078		-0.010		0.068
		(0.537)		(0.283)		(0.887)		(0.305)
Relative time [0,+5]	-0.013	-0.013	-0.393**	-0.393**	-0.397**	-0.397**	0.670***	0.670***
	(0.894)	(0.894)	(0.044)	(0.044)	(0.046)	(0.046)	(0.001)	(0.001)
Relative time [+10,+15]		0.214**		0.202**		-0.101		0.132*
		(0.029)		(0.019)		(0.261)		(0.100)
Relative time [+10, +20]	0.180**		0.190**		-0.083		0.106	
	(0.031)		(0.013)		(0.253)		(0.117)	
Relative time [+20,+60]		0.073		0.011		-0.110**		0.031
		(0.132)		(0.794)		(0.022)		(0.458)
Relative time [+25,+60]	0.069		-0.008		-0.118**		0.028	
	(0.172)		(0.846)		(0.021)		(0.524)	
Constant	-0.159***	-0.159***	0.011	0.011	0.254***	0.254***	-0.112	-0.112
	(0.005)	(0.005)	(0.768)	(0.770)	(0.000)	(0.000)	(0.143)	(0.143)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,518	7,518	7,544	7,544	7,558	7,558	7,439	7,439
R-squared (within)	0.0109	0.0111	0.0068	0.0066	0.0065	0.0065	0.1101	0.1101

Panel B: Positive Events (# 168)

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.026		-0.010		-0.042		0.004	
	(0.486)		(0.793)		(0.259)		(0.890)	
Relative time [-60,-15]		0.018		-0.022		-0.043		0.005
		(0.611)		(0.556)		(0.240)		(0.865)
Relative time [-15,-5]	-0.033		-0.086		-0.047		-0.036	
	(0.565)		(0.145)		(0.379)		(0.437)	
Relative time [-10,-5]		-0.022		-0.063		-0.047		-0.058
		(0.742)		(0.364)		(0.467)		(0.241)
Relative time [0,+5]	0.257**	0.257**	-0.100	-0.100	-0.469***	-0.469***	0.587***	0.587***
	(0.048)	(0.048)	(0.467)	(0.467)	(0.001)	(0.001)	(0.000)	(0.000)
Relative time [+10,+15]		-0.201**		-0.033		0.225***		0.110
		(0.023)		(0.700)		(0.009)		(0.103)
Relative time [+10, +20]	-0.080		0.065		0.160**		0.154***	
	(0.295)		(0.349)		(0.036)		(0.006)	
Relative time [+20,+60]		-0.010		-0.019		0.001		0.048
		(0.805)		(0.652)		(0.974)		(0.202)
Relative time [+25,+60]	-0.030		-0.053		-0.002		0.024	
	(0.434)		(0.206)		(0.948)		(0.546)	
Constant	-0.062	-0.062	0.047	0.047	0.142*	0.142*	-0.084	-0.084
	(0.293)	(0.293)	(0.296)	(0.296)	(0.071)	(0.071)	(0.106)	(0.105)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,660	7,660	7,712	7,712	7,641	7,641	7,525	7,525
R-squared (within)	0.0293	0.0300	0.0119	0.0115	0.0193	0.0196	0.1278	0.1274

Table A4: Panel regressions results on the behavior of retail investors around macroeconomic news announcements by using by using Menkhoff et al. (2016), standardization method.

Table A4.1: Table A4.1 is similar to Table 4 in the main text but it reports results by using by using Menkhoff et al. (2016), standardization method. We standardize order flow by dividing by its 1-week-standard deviation, $\frac{V}{\sigma}$. In this table the dependent variable is the behavior of individual investors and independent variables are the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 162)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.029		0.004		-0.051		0.073	
	(0.489)		(0.923)		(0.145)		(0.155)	
Relative time [-60,-15]		0.028		0.003		-0.052		0.059
		(0.485)		(0.946)		(0.132)		(0.179)
Relative time [-15,-5]	-0.027		-0.038		-0.025		0.010	
	(0.641)		(0.471)		(0.679)		(0.837)	
Relative time [-10,-5]		-0.052		-0.052		-0.007		0.048
		(0.472)		(0.448)		(0.922)		(0.434)
Relative time [0,+5]	-0.025	-0.025	-0.364**	-0.364**	-0.320**	-0.320**	0.612***	0.612***
	(0.797)	(0.797)	(0.028)	(0.028)	(0.043)	(0.043)	(0.000)	(0.000)
Relative time [+10,+15]		0.231**		0.205**		-0.116		0.118
		(0.018)		(0.020)		(0.211)		(0.127)
Relative time [+10, +20]	0.189**		0.206***		-0.087		0.094	
	(0.021)		(0.005)		(0.244)		(0.139)	
Relative time [+20,+60]		0.075*		0.012		-0.116**		0.035
		(0.096)		(0.763)		(0.015)		(0.367)
Relative time [+25,+60]	0.072		-0.012		-0.127**		0.033	
	(0.123)		(0.769)		(0.012)		(0.417)	
Constant	-0.145***	-0.145***	0.019	0.018	0.256***	0.256***	0.119**	0.119**
	(0.006)	(0.006)	(0.577)	(0.580)	(0.000)	(0.000)	(0.018)	(0.017)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,518	7,518	7,544	7,544	7,558	7,558	7,439	7,439
R-squared (within)	0.0110	0.0112	0.0078	0.0074	0.0066	0.0066	0.1215	0.1215
Panel B: Positive Events (# 168)								
	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.020		-0.018		-0.040		-0.001	
	(0.595)		(0.644)		(0.298)		(0.963)	
Relative time [-60,-15]		0.013		-0.027		-0.039		0.002
		(0.726)		(0.450)		(0.290)		(0.936)
Relative time [-15,-5]	-0.040		-0.091*		-0.047		-0.038	
	(0.468)		(0.094)		(0.394)		(0.394)	
Relative time [-10,-5]		-0.032		-0.080		-0.052		-0.072
		(0.610)		(0.220)		(0.418)		(0.131)
Relative time [0,+5]	0.252**	0.252**	-0.074	-0.074	-0.450***	-0.450***	0.574***	0.574***
	(0.041)	(0.041)	(0.549)	(0.548)	(0.000)	(0.000)	(0.000)	(0.000)
Relative time [+10,+15]		-0.208**		-0.051		0.211**		0.106
		(0.024)		(0.551)		(0.016)		(0.110)
Relative time [+10, +20]	-0.077		0.063		0.154**		0.160***	
	(0.327)		(0.370)		(0.048)		(0.005)	
Relative time [+20,+60]		-0.004		-0.012		-0.008		0.058
		(0.918)		(0.782)		(0.844)		(0.134)
Relative time [+25,+60]	-0.027		-0.049		-0.014		0.031	
	(0.493)		(0.250)		(0.733)		(0.445)	
Constant	-0.068	-0.068	0.041	0.041	0.159**	0.159**	0.118**	0.118**
	(0.224)	(0.224)	(0.405)	(0.406)	(0.036)	(0.036)	(0.012)	(0.012)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,660	7,660	7,712	7,712	7,641	7,641	7,525	7,525
R-squared (within)	0.0275	0.0282	0.0081	0.0077	0.0171	0.0173	0.1505	0.1502

Table A4.2: Table A4.2 is similar to Table 4 in the main text but it reports results by using by using Menkhoff et al. (2016), standardization method. We standardize order flow by dividing by its 1-month-standard deviation, $\frac{V}{\sigma}$. In this table the dependent variable is the behavior of individual investors and independent variables are the dummy variables capturing the relative time of interest as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore results are reported separately for each category. Panel A (Panel B) reports, panel regression coefficients for negative (positive) surprise events along with the level of their statistical significance. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively. p-values are reported in parenthesis.

Panel A: Negative Events (# 162)

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.038		0.009		-0.056*		0.065	
	(0.336)		(0.826)		(0.096)		(0.215)	
Relative time [-60,-15]		0.039		0.010		-0.057*		0.051
		(0.308)		(0.797)		(0.086)		(0.250)
Relative time [-15,-5]	-0.016		-0.047		-0.028		0.020	
	(0.787)		(0.397)		(0.635)		(0.703)	
Relative time [-10,-5]		-0.047		-0.078		-0.010		0.068
		(0.537)		(0.282)		(0.885)		(0.311)
Relative time [0,+5]	-0.013	-0.013	-0.393**	-0.393**	-0.398**	-0.398**	0.669***	0.669***
	(0.895)	(0.895)	(0.044)	(0.044)	(0.046)	(0.046)	(0.001)	(0.001)
Relative time [+10,+15]		0.214**		0.202**		-0.101		0.130
		(0.029)		(0.019)		(0.260)		(0.103)
Relative time [+10, +20]	0.180**		0.190**		-0.084		0.104	
	(0.031)		(0.013)		(0.252)		(0.121)	
Relative time [+20,+60]		0.074		0.011		-0.110**		0.029
		(0.131)		(0.797)		(0.022)		(0.478)
Relative time [+25,+60]	0.069		-0.008		-0.118**		0.026	
	(0.170)		(0.843)		(0.021)		(0.547)	
Relative time (t+5, t+12)								
Relative time (t+6, t+12)								
Constant	-0.164***	-0.164***	0.012	0.012	0.263***	0.263***	0.110	0.110
	(0.004)	(0.004)	(0.742)	(0.744)	(0.000)	(0.000)	(0.111)	(0.111)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,518	7,518	7,544	7,544	7,558	7,558	7,439	7,439
R-squared (within)	0.0110	0.0111	0.0068	0.0066	0.0066	0.0066	0.1121	0.1120

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60,-20]	0.026		-0.011		-0.042		-0.001	
	(0.491)		(0.790)		(0.265)		(0.974)	
Relative time [-60,-15]		0.018		-0.022		-0.043		0.000
		(0.617)		(0.552)		(0.246)		(0.998)
Relative time [-15,-5]	-0.033		-0.086		-0.047		-0.039	
	(0.559)		(0.143)		(0.383)		(0.389)	
Relative time [-10,-5]		-0.022		-0.063		-0.047		-0.062
		(0.737)		(0.363)		(0.471)		(0.212)
Relative time [0,+5]	0.256**	0.256**	-0.101	-0.101	-0.469***	-0.469***	0.584***	0.584***
	(0.049)	(0.049)	(0.466)	(0.466)	(0.001)	(0.001)	(0.000)	(0.000)
Relative time [+10,+15]		-0.202**		-0.034		0.225***		0.104
		(0.022)		(0.698)		(0.009)		(0.126)
Relative time [+10, +20]	-0.080		0.065		0.161**		0.148***	
	(0.292)		(0.350)		(0.036)		(0.008)	
Relative time [+20,+60]		-0.010		-0.019		0.002		0.041
		(0.797)		(0.645)		(0.967)		(0.268)
Relative time [+25,+60]	-0.031		-0.053		-0.002		0.016	
	(0.427)		(0.202)		(0.955)		(0.674)	
Constant	-0.064	-0.064	0.044	0.044	0.143*	0.143*	0.101**	0.101**
	(0.292)	(0.292)	(0.338)	(0.339)	(0.068)	(0.068)	(0.035)	(0.035)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Time of the Day dummies	YES	YES	YES	YES	YES	YES	YES	YES
Day of the Week dummies	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,660	7,660	7,712	7,712	7,641	7,641	7,525	7,525
R-squared (within)	0.0295	0.0302	0.0119	0.0114	0.0192	0.0195	0.1408	0.1404

Table A5: Panel regressions results on the behavior of retail investors around macroeconomic news announcements for both positive and negative surprise events.

This table presents panel regression results for both positive and negative surprise events. In Model 1, the dependent variable is the behavior of individual investors and as independent variables it includes the dummy variables capturing the relative time of interest, as well as lags of our dependent variable. The optimal number of lags is determined by using the Schwartz and Akaike information criteria. We are using Net Order Flow, Net Long, Net Short and Overall Unsigned Volume as proxies for retail investors overall behavior. Dummy variables capture the relative time of interest in minutes. For analysis purposes, using the announcements' surprise component, we classified them into two main categories, positive and negative surprise events (detailed description on Section 3.1.2.) therefore a dummy variable that captures the sing of the surprise of the event is created (d_pos=1 if we have positive surprise event and d_pos=0, otherwise). Interactions between the dummy variable (d_pos) and the relative time of interest are also contacted. Model 2, in addition to the predetermined independent variables in Model 1, it also controls for past returns. Panel regression coefficients along with their p-values (in parenthesis) are reported. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

	Net Order Flow		Net Long		Net Short		Overall Unsigned Volume	
Independent Variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Relative time [-60, -15]	0.110	0.069	0.022	-0.009	-0.112	-0.093	0.098	0.101
	(0.314)	(0.508)	(0.774)	(0.904)	(0.125)	(0.177)	(0.345)	(0.333)
Relative time [-10, -5]	-0.106	-0.152	-0.136	-0.169	-0.029	-0.021	-0.004	-0.003
	(0.561)	(0.373)	(0.249)	(0.149)	(0.834)	(0.877)	(0.979)	(0.983)
Relative time [0, 5]	0.003	-0.020	-0.678**	-0.680**	-0.691**	-0.675**	1.616***	1.619***
	(0.992)	(0.947)	(0.039)	(0.042)	(0.028)	(0.035)	(0.003)	(0.003)
Relative time [+10,+15]	0.525**	0.124	0.362**	0.146	-0.179	0.010	0.284	0.300
	(0.049)	(0.637)	(0.022)	(0.342)	(0.347)	(0.958)	(0.222)	(0.192)
Relative time [+20,+60]	0.218**	0.137	0.048	-0.009	-0.227***	-0.177**	-0.017	-0.008
	(0.044)	(0.145)	(0.520)	(0.901)	(0.009)	(0.018)	(0.863)	(0.937)
d_pos	0.044	-0.000	0.031	0.007	-0.009	0.010	0.068	0.071
	(0.591)	(0.997)	(0.595)	(0.903)	(0.875)	(0.850)	(0.335)	(0.310)
d_pos*Relative time [-60, -15]	-0.090	-0.023	-0.077	-0.041	0.016	-0.021	-0.115	-0.121
	(0.580)	(0.880)	(0.486)	(0.694)	(0.892)	(0.848)	(0.371)	(0.350)
d_pos*Relative time [-10, -5]	0.098	0.108	-0.008	-0.010	-0.137	-0.120	-0.170	-0.173
	(0.717)	(0.667)	(0.963)	(0.954)	(0.498)	(0.540)	(0.431)	(0.422)
d_pos*Relative time [0, 5]	0.819*	0.806*	0.548	0.534	-0.247	-0.272	-0.125	-0.120
	(0.061)	(0.067)	(0.166)	(0.183)	(0.561)	(0.526)	(0.847)	(0.853)
d_pos*Relative time [+10,+15]	-1.281***	-0.685*	-0.534**	-0.220	0.649**	0.420	0.059	0.034
	(0.001)	(0.052)	(0.031)	(0.339)	(0.013)	(0.107)	(0.853)	(0.914)
d_pos*Relative time [+20,+60]	-0.268	-0.135	-0.097	-0.007	0.221*	0.151	0.096	0.079
	(0.108)	(0.376)	(0.393)	(0.951)	(0.086)	(0.195)	(0.481)	(0.557)
Constant	-0.219**	-0.231**	0.055	0.061	0.336***	0.347***	0.174	0.172
	(0.038)	(0.027)	(0.388)	(0.326)	(0.000)	(0.000)	(0.105)	(0.113)
Lags of Dependent Variable	YES	YES	YES	YES	YES	YES	YES	YES
Lag Returns	NO	YES	NO	YES	NO	YES	NO	YES
Time_of_the_Day	YES	YES	YES	YES	YES	YES	YES	YES
Day_of_the_Week	YES	YES	YES	YES	YES	YES	YES	YES
Country_FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	15,197	15,162	15,278	15,175	15,300	15,162	14,981	14,978
R-squared	0.0230	0.0929	0.0060	0.0439	0.0081	0.0460	0.1539	0.1542

Table A6: Time Series analysis for the impact of sentiment on individual investors' behavior by using a different EU to US relative TRMI sentiment measure.

Table A6 is similar to Table 6 in the main text but it reports results by using a the ratio between EU and US sentiment index (Hafez, 2013), $\mathrm{Ratio\_EUvsUS}_t = \frac{\mathbf{\Delta S\_EU}_t}{\mathbf{\Delta S\_US}_t}$, where ΔS_EU_t (ΔS_US_t) is the EU (US) change in TRMI sentiment at t. The TRMI sentiment index is normalized with a scale between -1 to 1 and having negative numbers on the denominator can lead to misleading results, therefore we convert our sentiment variables into positive numbers, with a scale from 0 to 100. This table presents time series regressions' results, where the dependent variable is the behavior of individual investors (as captured by individuals' Net Order Flow) and as independent variables the rolling 30-minute lagged sentiment change. Model 1 includes the rolling 30-minute lagged sentiment change and the 12, 5-minute lagged EURUSD exchange rate returns. Model 3 includes the rolling 30-minute lagged sentiment change and the exchange rate return over the prior 5 minute, ΔR_{t-1}, and over the prior 12 minutes, $\Delta R_{t-2,\ t-12}$. Model 2 and Model 4, in addition to the predetermined independent variables in Model 1 and Model 3 respectively, it also considers the macro news' dummy variables which capture the macroeconomic announcements' impact. Dummy variables created to capture the impact for the time period [-60min, +60min]. Time series' regression coefficients and p-values (in parenthesis) are reported. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

Independent Variables	Model 1	Model 2	Model 2	Model 4
Lagged-Rolling 30-min	58.317***	61.066***	58.385***	61.139***
Sentiment Change	(0.008)	(0.006)	(0.008)	(0.006)
Lagged Returns				
ΔR_{t-1}	-16.974***		-16.978***	
	(0.000)		(0.000)	
ΔR_{t-2}	-9.121***		-9.123***	
	(0.000)		(0.000)	
ΔR_{t-3}	-5.105***		-5.104***	
	(0.000)		(0.000)	
ΔR_{t-4}	-2.988***		-2.985***	
	(0.000)		(0.000)	
ΔR_{t-5}	-2.485***		-2.482***	
	(0.000)		(0.000)	
ΔR_{t-6}	-1.425***		-1.425***	
	(0.000)		(0.000)	
ΔR_{t-7}	-1.159***		-1.166***	
	(0.001)		(0.000)	
ΔR_{t-8}	-0.554*		-0.555*	
	(0.073)		(0.073)	
ΔR_{t-9}	-0.641**		-0.643**	
	(0.046)		(0.045)	
ΔR_{t-10}	-0.622**		-0.629**	
	(0.037)		(0.034)	
ΔR_{t-11}	-0.617*		-0.622*	
	(0.073)		(0.071)	
ΔR_{t-12}	-0.665**		-0.668**	
	(0.030)		(0.029)	
ΔR_{t-1}		-16.753***		-16.748***
		(0.000)		(0.000)
$\Delta R_{t-2,\ t-12}$		-1.821***		-1.819***
		(0.000)		(0.000)
Constant	-0.042	-0.030	-0.046	-0.032
	(0.153)	(0.298)	(0.115)	(0.262)
Lags of Dependent Variable	Yes	Yes	Yes	Yes
Macro News	No	No	Yes	Yes
Hour_of_the_Day	Yes	Yes	Yes	Yes
Day_of_the_Week	Yes	Yes	Yes	Yes
Observations	126,052	126,700	126,052	126,700
Adjusted R-squared	0.0752	0.0574	0.0755	0.0578

Table A7: Time Series analysis for the impact of sentiment on individual investors' behavior by using Menkhoff et al. (2016), standardization method.

Table A7.1: Table A7.1 is similar to Table 6 in the main text but it reports results by using by using Menkhoff et al. (2016), standardization method. We standardize order flow by dividing by its 1-week-standard deviation, $\frac{V}{\sigma}$. This table presents time series regressions' results, where the dependent variable is the behavior of individual investors (as captured by individuals' Net Order Flow) and as independent variables the rolling 30-minute lagged sentiment change. Model 1 includes the rolling 30-minute lagged sentiment change and the 12, 5-minute lagged EURUSD exchange rate returns. Model 3 includes the rolling 30-minute lagged sentiment change and the exchange rate return over the prior 5 minute, ΔR_{t-1}, and over the prior 12 minutes, $\Delta R_{t-2,\,t-12}$. Model 2 and Model 4, in addition to the predetermined independent variables in Model 1 and Model 3 respectively, it also considers the macro news' dummy variables which capture the macroeconomic announcements' impact. Dummy variables created to capture the impact for the time period [-60min, +60min]. Time series' regression coefficients and p-values (in parenthesis) are reported. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

Independent Variables	Model 1	Model 2	Model 3	Model 4
Lagged-Rolling 30-min	8.792**	9.155**	8.784**	9.147**
Sentiment Change	(0.032)	(0.028)	(0.032)	(0.027)
Lagged Returns				
ΔR_{t-1}	-5.705***		-5.705***	
	(0.000)		(0.000)	
ΔR_{t-2}	-3.152***		-3.150***	
	(0.000)		(0.000)	
ΔR_{t-3}	-1.777***		-1.778***	
	(0.000)		(0.000)	
ΔR_{t-4}	-1.013***		-1.013***	
	(0.000)		(0.000)	
ΔR_{t-5}	-0.924***		-0.923***	
	(0.000)		(0.000)	
ΔR_{t-6}	-0.490***		-0.490***	
	(0.000)		(0.000)	
ΔR_{t-7}	-0.426***		-0.428***	
	(0.000)		(0.000)	
ΔR_{t-8}	-0.248**		-0.248**	
	(0.011)		(0.011)	
ΔR_{t-9}	-0.172		-0.173	
	(0.107)		(0.104)	
ΔR_{t-10}	-0.218**		-0.221**	
	(0.022)		(0.020)	
ΔR_{t-11}	-0.211**		-0.213**	
	(0.047)		(0.045)	
ΔR_{t-12}	-0.208**		-0.209**	
	(0.027)		(0.026)	
ΔR_{t-1}		-5.624***		-5.620***
		(0.000)		(0.000)
$\Delta R_{t-2,\,t-12}$		-0.634***		-0.634***
		(0.000)		(0.000)
Constant	-0.013	-0.010	-0.015	-0.010
	(0.196)	(0.349)	(0.157)	(0.323)
Lags of Dependent Variable	Yes	Yes	Yes	Yes
Macro News	No	No	Yes	Yes
Hour_of_the_Day	Yes	Yes	Yes	Yes
Day_of_the_Week	Yes	Yes	Yes	Yes
Observations	126,052	126,700	126,052	126,700
Adjusted R-squared	0.0727	0.0545	0.0731	0.0549

Table A7.2: Table A7.2 is similar to Table 6 in the main text but it reports results by using by using Menkhoff et al. (2016), standardization method. We standardize order flow by dividing by its 1-month-standard deviation, $\frac{V}{\sigma}$. This table presents time series regressions' results, where the dependent variable is the behavior of individual investors (as captured by individuals' Net Order Flow) and as independent variables the rolling 30-minute lagged sentiment change. Model 1 includes the rolling 30-minute lagged sentiment change and the 12, 5-minute lagged EURUSD exchange rate returns. Model 3 includes the rolling 30-minute lagged sentiment change and the exchange rate return over the prior 5 minute, ΔR_{t-1}, and over the prior 12 minutes, $\Delta R_{t-2, t-12}$. Model 2 and Model 4, in addition to the predetermined independent variables in Model 1 and Model 3 respectively, it also considers the macro news' dummy variables which capture the macroeconomic announcements' impact. Dummy variables created to capture the impact for the time period [-60min, +60min]. Time series' regression coefficients and p-values (in parenthesis) are reported. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

Independent Variables	Model 1	Model 2	Model 3	Model 4
Lagged-Rolling 30-min	7.710*	8.273**	7.695*	8.258**
Sentiment Change	(0.059)	(0.045)	(0.059)	(0.045)
Lagged Returns				
ΔR_{t-1}	-5.642***		-5.642***	
	(0.000)		(0.000)	
ΔR_{t-2}	-3.131***		-3.130***	
	(0.000)		(0.000)	
ΔR_{t-3}	-1.788***		-1.790***	
	(0.000)		(0.000)	
ΔR_{t-4}	-1.050***		-1.051***	
	(0.000)		(0.000)	
ΔR_{t-5}	-0.929***		-0.929***	
	(0.000)		(0.000)	
ΔR_{t-6}	-0.529***		-0.529***	
	(0.000)		(0.000)	
ΔR_{t-7}	-0.440***		-0.442***	
	(0.000)		(0.000)	
ΔR_{t-8}	-0.259**		-0.260***	
	(0.010)		(0.010)	
ΔR_{t-9}	-0.174		-0.176	
	(0.135)		(0.131)	
ΔR_{t-10}	-0.203*		-0.206**	
	(0.050)		(0.046)	
ΔR_{t-11}	-0.251**		-0.254**	
	(0.023)		(0.022)	
ΔR_{t-12}	-0.171*		-0.172*	
	(0.088)		(0.085)	
ΔR_{t-1}		-5.565***		-5.562***
		(0.000)		(0.000)
$\Delta R_{t-2, t-12}$		-0.646***		-0.646***
		(0.000)		(0.000)
Constant	-0.014	-0.010	-0.015	-0.011
	(0.171)	(0.318)	(0.137)	(0.294)
Lags of Dependent Variabl	Yes	Yes	Yes	Yes
Macro News	No	No	Yes	Yes
Hour_of_the_Day	Yes	Yes	Yes	Yes
Day_of_the_Week	Yes	Yes	Yes	Yes
Observations	126,052	126,700	126,052	126,700
Adjusted R-squared	0.0683	0.0505	0.0685	0.0507

Table A8: Trading Strategy results when using different short term moving average of Net Order Flow.

Table A8.1: This table is similar to Table 7 in the main text but it reports results by using different short term moving average of Net Order Flow. It presents mean and median return of the in-sample and out-of-sample, simple cross over trading strategy that generates buy and sell signals opposite to that indicated by individual investors Net Order Flow. It generates sell signals of EURUSD when the short term (4 hours) moving average of Net Order Flow crosses above the long term (daily) moving average of Net Order Flow and buy signals of EURUSD when the short term (4 hours) moving average of Net Order Flow crosses below the long term (daily) moving average of Net Order Flow. We then calculate the mean and median log returns on EURUSD for holding period 1 to 20 hours for non-overlapping signals. Panel A (Panel B) reports mean and median results along with the level of their statistical significance (SS), for the in-sample (out-of-sample) analysis. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

		Panel A: Cross- Over Strategy - In-Sample					Panel B: Cross- Over Strategy - Out-of-Sample				
Holding period	Strategy signal	N	Mean	SS	Median	SS	N	Mean	SS	Median	SS
1 hour	long	181	0.008		-0.003		189	-0.001		-0.009	
1 hour	short	192	-0.003		0.000		186	0.009		0.009	
2 hours	long	173	0.025		0.007		173	0.014		-0.002	
2 hours	short	174	0.005		-0.012		181	0.017		0.015	
3 hours	long	160	0.034	*	0.014	*	163	0.029	**	0.019	**
3 hours	short	161	0.029		0.011		163	0.012		-0.005	
4 hours	long	145	0.055	**	0.025	**	147	0.027	*	0.021	**
4 hours	short	149	0.033	*	0.011		149	0.036	*	0.023	**
5 hours	long	137	0.077	***	0.027	**	139	0.031		0.020	**
5 hours	short	134	0.038		-0.003		136	0.050	**	0.052	***
6 hours	long	125	0.062	**	0.032	**	125	0.035		0.014	*
6 hours	short	129	0.051	*	0.015	*	127	0.056	**	0.042	**
7 hours	long	115	0.078	**	0.025	**	108	0.036		0.043	*
7 hours	short	120	0.060	*	0.025	*	117	0.054	*	0.027	*
8 hours	long	107	0.108	***	0.056	***	100	0.068	*	0.077	***
8 hours	short	115	0.063	*	0.035	**	111	0.019		0.016	
9 hours	long	100	0.104	**	0.044	***	94	0.083	**	0.076	***
9 hours	short	110	0.074	*	0.046	**	104	0.052		0.063	*
10 hours	long	93	0.104	**	0.059	***	87	0.114	***	0.138	***
10 hours	short	101	0.081	*	0.050	**	92	0.085	**	0.064	**
11 hours	long	83	0.144	***	0.097	***	83	0.139	***	0.154	***
11 hours	short	93	0.072		0.049		86	0.114	***	0.099	***
12 hours	long	75	0.187	***	0.151	***	74	0.135	***	0.151	***
12 hours	short	85	0.089	*	0.043	*	77	0.156	***	0.124	***
13 hours	long	67	0.194	***	0.160	***	67	0.135	***	0.206	***
13 hours	short	79	0.136	***	0.055	**	71	0.190	***	0.183	***
14 hours	long	64	0.150	**	0.092	**	61	0.196	***	0.244	***
14 hours	short	71	0.185	***	0.107	***	66	0.200	***	0.197	***
15 hours	long	54	0.242	***	0.169	***	59	0.218	***	0.240	***
15 hours	short	69	0.179	***	0.115	***	62	0.226	***	0.171	***
16 hours	long	48	0.306	***	0.199	***	54	0.231	***	0.236	***
16 hours	short	65	0.181	***	0.077	***	59	0.205	***	0.137	***
17 hours	long	43	0.350	***	0.242	***	52	0.229	***	0.224	***
17 hours	short	60	0.177	***	0.071	***	55	0.188	***	0.147	***
18 hours	long	39	0.384	***	0.313	***	46	0.229	***	0.281	***
18 hours	short	57	0.207	***	0.069	***	46	0.225	***	0.169	***
19 hours	long	37	0.353	***	0.353	***	38	0.250	***	0.341	***
19 hours	short	52	0.226	***	0.123	***	42	0.245	***	0.176	***
20 hours	long	34	0.404	***	0.321	***	30	0.278	***	0.414	***
20 hours	short	47	0.253	***	0.136	***	39	0.255	***	0.253	***

Table A8.2: This table is similar to Table 7 in the main text but it reports results by using different short term moving average of Net Order Flow. It presents mean and median return of the in-sample and out-of-sample, simple cross over trading strategy that generates buy and sell signals opposite to that indicated by individual investors Net Order Flow. It generates sell signals of EURUSD when the short term (6 hours) moving average of Net Order Flow crosses above the long term (daily) moving average of Net Order Flow and buy signals of EURUSD when the short term (6 hours) moving average of Net Order Flow crosses below the long term (daily) moving average of Net Order Flow. We then calculate the mean and median log returns on EURUSD for holding period 1 to 20 hours for non-overlapping signals. Panel A (Panel B) reports mean and median results along with the level of their statistical significance (SS), for the in-sample (out-of-sample) analysis. ***, ** and * denote statistical significance at the 1%, 5%, 10% level, respectively.

		Panel A: Cross- Over Strategy - In-Sample					Panel B: Cross- Over Strategy - Out-of-Sample				
Holding period	Strategy signal	N	Mean	SS	Median	SS	N	Mean	SS	Median	SS
1 hour	long	160	0.025	**	0.015	**	170	0.015	*	0.009	
1 hour	short	164	-0.016		-0.004		169	0.003		-0.004	
2 hours	long	148	0.037	**	0.017	*	161	0.009		0.002	
2 hours	short	150	-0.005		0.000		157	-0.005		0.006	
3 hours	long	141	0.046	**	0.015	*	150	0.013		0.009	
3 hours	short	144	0.015		0.001		152	0.005		-0.014	
4 hours	long	135	0.045	*	0.014	*	145	-0.011		-0.001	
4 hours	short	136	0.026		0.012		139	0.010		-0.002	
5 hours	long	129	0.055	**	0.022		135	0.002		0.008	
5 hours	short	130	0.038		0.014		131	-0.015		-0.014	
6 hours	long	123	0.063	**	0.024	**	129	-0.017		-0.011	
6 hours	short	123	0.047		0.027	*	125	-0.020		-0.023	
7 hours	long	118	0.063	*	0.044	**	108	0.020		0.044	*
7 hours	short	116	0.061	*	0.023	*	117	0.001		-0.010	
8 hours	long	112	0.087	**	0.075	***	104	0.022		0.062	*
8 hours	short	112	0.055		0.024	*	109	0.003		0.002	
9 hours	long	103	0.095	**	0.065	***	96	0.087	***	0.078	***
9 hours	short	107	0.084	**	0.035	**	106	0.017		0.011	
10 hours	long	98	0.090	**	0.069	**	89	0.109	***	0.090	***
10 hours	short	105	0.073	*	0.028	*	100	0.036		0.029	
11 hours	long	89	0.101	**	0.084	**	86	0.114	***	0.132	***
11 hours	short	97	0.085	*	0.043	**	93	0.087	**	0.044	**
12 hours	long	78	0.126	**	0.107	**	81	0.118	***	0.154	***
12 hours	short	88	0.087	*	0.045	*	85	0.126	***	0.079	***
13 hours	long	72	0.138	**	0.104	**	73	0.112	**	0.186	***
13 hours	short	75	0.171	***	0.110	***	75	0.129	***	0.097	***
14 hours	long	67	0.150	**	0.143	***	67	0.162	***	0.235	***
14 hours	short	71	0.163	***	0.125	***	71	0.158	***	0.108	***
15 hours	long	60	0.206	***	0.159	***	64	0.192	***	0.221	***
15 hours	short	67	0.171	***	0.104	***	64	0.172	***	0.145	***
16 hours	long	50	0.315	***	0.224	***	59	0.200	***	0.233	***
16 hours	short	62	0.189	***	0.097	***	60	0.153	***	0.120	***
17 hours	long	49	0.334	***	0.217	***	53	0.211	***	0.267	***
17 hours	short	60	0.204	***	0.107	***	56	0.174	***	0.162	***
18 hours	long	43	0.332	***	0.257	***	43	0.232	***	0.285	***
18 hours	short	54	0.259	***	0.136	***	48	0.218	***	0.161	***
19 hours	long	39	0.317	***	0.280	***	37	0.286	***	0.385	***
19 hours	short	52	0.272	***	0.113	***	44	0.235	***	0.230	***
20 hours	long	37	0.371	***	0.313	***	32	0.332	***	0.368	***
20 hours	short	43	0.290	***	0.211	***	40	0.251	***	0.279	***

Chapter 2

Heterogeneous risk-taking behavior among retailers.

Chapter 2: Heterogeneous risk-taking behavior among retailers.

Abstract

Using leverage level, a widely used mechanism in the forex market, we obtain a direct dimension to explore investors' attitude toward risk. We analyze a detail proprietary trade by trade data of Foreign Exchange (FX) retail investors and show that, consistent with existing literature, young, educated investors, with higher employment status and very high income and net worth are willing to accept higher levels of risk. Results on the continent of residence indicate that Asian traders are generally engaged in greater risk levels, followed by Africans, Europeans, Americans and finally traders from Oceania. The willingness of women to accept higher levels of risk than men do, is an unexpected derived outcome, implying that females in FX markets are significantly different from females in equity markets. Splitting by gender and examining how individuals adjust their risk-taking behavior based on past performance, evidence reveals that men exhibit self-attribution bias. Reported gender difference diminishes, after comparing the risk adjusted behavior of women with a control sample of men, based on demographic characteristics, demonstrating that the reported distinction arises mainly from other demographic differences and not gender per se. More precisely, we show that characteristics portraying sophisticated investors decrease the probability of exhibition of self-attribution.

1. Introduction

Risk taking behavior is a fundamental element on the determination of investment decisions. Increased risk is associated with increased return but at the same time, misunderstanding and mismanagement of risk can lead to significant wealth reductions. In the simplest case, an individual's decision can notably affect only his own standard of living whereas, in the case in which he may be a financial services planner, an investment advisor or a manager of an organization, it can affect the performance and the standard of living of various society members.

The aim of this project is to investigate the attitude of retail investors toward risk. One of our key innovations is the use of leverage level[41], a widely used mechanism in forex market to obtain a direct dimension and explore investors risk taking behavior. More specifically, we examine whether demographic factors such as age, gender, educational level, employment status, income, net worth and geographical region, differentiate investors willingness to accept risk as well as the way that past performance affect adjustments to their risk taking behavior.

Measuring financial risk taking is very important, nevertheless in practice there is a difficulty with its empirical investigation due to the subjective nature of risk taking and the variation in the techniques used to examine this phenomenon. Numerous risk taking proxies were developed from different fields of research, such as psychology, economics and finance through the analysis of experiments and surveys (see, Cohn et al., 1975, Arkes et al.,1988, Grable, 2000, Dwyer et al., 2002, Borghans et al., 2009, Charness et al., 2009, Charness and Gneezy, 2010, Hoffmann et al., 2015), with the usage of the utility function (see, Arrow, 1964, Pratt, 1965, Jianakoplos and Bernasek, 1998, Halek and Eisenhauer, 2001, Holt and Laury, 2002), with the examination of investments' characteristics, like the degree of diversification, investments' volatility, beta and size of investments, (see, Barber

[41] Leverage enables a trader to control a larger amount of capital in a trade by using a relatively small amount of his own, magnifying at the same time both, gains and losses. Forex market offer the higher leverage levels that investor can obtain in financial markets. For the sample period under investigation, forex firms can offer a leverage that can came up to the very high of 1:1000, or even higher.

and Odean, 2001, Goetzmann and Kumar, 2008, Ben David et. al., 2018) or with the employment of other approaches.

Individual investors trading activity, behavior and performance is attracting the attention of market practitioners and academics with more recent studies trying to differentiate their response with the use of demographic characteristics[42]. Understanding how risk-taking behavior differentiates among individuals is beneficial for retail investors and for financial services planners and investment advisors. Retailers knowing how their risk-taking behavior is affected, can avoid misleading risk taking while knowledge of heterogeneous risk taking behavior formation, would be helpful for financial services planners and investment advisors, on the creation of risk-specific financial investment packages.

This study contributes to individual investors and behavioral finance literatures in three main ways. Firstly, it analyzes an up to date high frequency dataset to examine the behavior of retail investors in foreign exchange (FX) markets. Most of the empirical work on learning retail investors behavior concentrated on equity market data. It's important to examine separately the behavior of retail investors in FX market from equity market since it is difficult for an FX retail investor to acquire access into private information, which can significantly affect exchange rate movements. Moreover, the trading lifespan of each investor in our sample is much smaller relative to the investor of stock market and in addition, the forex market offers the highest leverage levels that an investor can obtain in financial markets. Differences in leverage across investors but also the use of differential leverage by the same investor lead to our second contribution, where by using leverage we can obtain a direct measure to examine individuals risk taking attitude. Finally, by using demographic characteristics we add to our understanding of heterogeneous risk-taking behavior among retail investors.

In our first set of tests, we employ cross sectional regression analysis on trade by trade data, dating from October 24th, 2014 to February 27th, 2018, for 31,906 individuals who account a total of 11,186,437 trades on currency pairs and gold. Evidence reveals that, consistent with psychology and finance literature, young, educated investors, with higher employment status and very high income and net worth are willing to accept higher levels

[42] See, Barber and Odean, (2000), Ivkovic and Weisbenner (2005); Graham and Kumar (2006); Goetzmann and Kumar (2008); Kumar (2009a, 2009b); Korniotis and Kumar (2011; 2013), Seasholes and Zhu (2010).

of risk. In addition, results regarding the continent of residence are proving that Asian traders are generally engaged in greater risk levels, followed by Africans, Europeans, Americans and finally traders from Oceania. Surprisingly, women are shown to be willing to accept higher level of risk than men do, an outcome which is persistent even when we compare women with a control sample of men, which identified based on demographic characteristics. Moreover, this implies that women in FX market are significantly different from women in equity markets. By controlling for the experience of each investor and interacting it with gender, we observed that as male investors gain experience, they increase their risk tolerance levels but with the overall effect on males being lower than that of females.

By utilizing the trading activity of investors with dual leverage, we extent our investigation on the risk attitude of individual investors by examining how retailers adjust their risk-taking behavior based on past performance. Motivated by our earlier unexpected result about risk taking behavior of women, we select gender to be the first demographic under examination. Therefore, we split our sample into male and female subsamples and results support that men exhibit self-attribution. Moving one step forward and implementing propensity score matching method to compare women over a control sample of men with closer demographic characteristics, we show that their behavioural differences arise mainly from demographic differences and not gender per se. The unobserved gender- behavioural difference is further testified when we increase the number of participants of the control group and notice that the corresponding sample still cannot be characterized by the exhibition of self-attribution bias. In contrast, the self-attribution bias effect is reflecting strong for the rest of the men, excluding those in the controlled group.

Finally, we attempt to identify which demographics differentiate the presence of self-attribution. To achieve our objective, we implement a logit regression analysis, in which the dependent variable is an indicator that takes the value of one if a trader exhibits self-attribution bias and zero otherwise. Documented results reveal that sophisticated investors are less prone to the bias and the effects appear to also be economically significant.

The remainder of the paper is organized as follows. Section 2 presents related literature. Next, Section 3 describes the dataset. Section 4, details methodology and discusses empirical results and Section 5 concludes.

2. Literature Review and Hypotheses Development

Risk taking behavior plays an essential component of financial decision making. Measuring financial risk taking is very important but in practice there is a difficulty with its empirical investigation due to its subjective nature and the flexibility on fluctuations of risk taking behavior. Thaler and Johnson, (1990) state that "making generalization about risk-taking preferences is difficult. General tendencies can be reversed by a simple reframing of options".

Several approaches from different fields of research, such as psychology, economics and finance have been developed in order to estimate investors risk taking behavior. Some proxies established through the analysis of experiments and surveys (see, Cohn et al., 1975, Arkes et al.,1988, Grable, 2000, Dwyer et al., 2002, Borghans et al., 2009, Charness et al., 2009, Charness and Gneezy, 2010, Hoffmann et al., 2015), other with the usage of the utility function (see, Arrow, 1964, Pratt,1965[43], Jianakoplos and Bernasek, 1998, Halek and Eisenhauer, 2001, Holt and Laury, 2002), other with the examination of investments' characteristics, like the degree of diversification, investments' volatility, beta and size of the investments (see, Barber and Odean, 2001, Goetzmann and Kumar, 2008, Ben David et. al., 2018) and other with the employment of different approaches. For example, Grinblatt and Keloharju, 2009, define sensation seekers as those who among other things are also searching for financial risk and estimate sensation seeking by the number of automobile speeding convictions earned by an investor over a multiyear period.

The comparison of risk taking behavior across different demographic characteristics is attracting the attention of academics, with demographic factors appearing to significantly influence individuals risk taking behavior. For example, Barber and Odean, (2001) construct four risk portfolio measures (individuals' portfolio volatility, individual stock volatility, beta and size of portfolio) to test whether men invest in riskier positions than women and consistent with their expectations, men are willing to accept more risk. Control variables such as marital status, age and income are also found to be negatively correlated with risk taking behaviour. In Goetzmann and Kumar, (2008) study, the authors state that there is a link between investors' risk taking behavior and their diversification decisions. Specifically, they support that investors' level of diversification will increase with investors'

[43] At the mid-1960, Arrow and Pratt define the now broadly used measures of risk aversion.

risk aversion. Reported results show that older, educated, sophisticated and highly paid investors are more likely to exhibit a higher preference for diversification. In an expanded analysis of the subject, Korniotis and Kumar (2010), declare that the effects of sophistication and cognitive abilities on individuals trading behavior are not straightforward. On the one hand they may choose to construct their portfolios following standard portfolio theory (holding well-diversified portfolios and adopt buy and hold strategies), whereas on the other hand increased sophistication amplifies their abilities to handle higher risk levels and beat various passive performance benchmarks. The second statement is further supported in Korniotis and Kumar (2013), where authors, based on 3 cognitive ability measures and investors demographic characteristics, developed a smartness estimate and show that "smart" investors depart from normative prescriptions of portfolio theory (exhibit more portfolio distortions like holding less diversified portfolios, trade more actively and exhibit stronger preference for local stocks), outperforming at the same time "dumb" investors. The positive relation between cognitive ability and willingness to take risk is also noted by Dohmen et al., (2010). Characteristics that Korniotis and Kumar (2013) define to represent smart investors, are the characteristics that psychology literature also evident to determine the probability for engagement in higher levels of risk. More specifically, evidence supports a decrease in risk taking as individuals grow and an increase as their education, income and wealth level increase (Zuckerman, 1994, Slovic, 1996, Palsson, 1996, Byrnes et al, 1999, Grable, 2000, Olsen and Cox, 2001, Chang et al., 2004, Fan and Xiao, 2006, Gardner et al., 2005, Lemaster and Strough, 2014, Fisher and Yao, 2017). Therefore, by cross sectionally investigating the risk taking behavior of individual investors across demographic characteristics and combining results from psychology and finance literature, we expect that for men and young investors, an increase on education level, employment status and income (wealth), will be positively associated with investors' willingness to accept higher levels of risks. Additionally, in reference to the work of Weber and Hsee (1998), Hsee and Weber (1999) and Fan and Xiao, (2006), risk-taking attitude is anticipated to be correlated with individuals' continent of residence. Especially, we expect a clear distinction between the risk taking behavior of Asians and Americans with the former to be willing to accept higher levels of risk and Europeans risk preferences to be placed somewhere in between.

Hypothesis 1: *Asians, men, young, educated, employed investors with higher income and wealth are more likely to engage in higher levels of risk.*

An association between risk taking behavior and biases is also confirmed in the behavioural literature. Empirical evidence shows that individuals tend to overestimate their personal skills, knowledge and predicted abilities for their investment performance and this can significantly affect their risk-taking behaviour. Significant strands of studies model the so-called overconfident traders,[44] with Odean (1998) establishing that overconfident investors hold riskier portfolios than rational investors do. A related bias to overconfidence is self-attribution bias. According to self-attribution bias, individuals overestimate internal characteristics such as skill and effort for success and blame external characteristics, such as bad luck, for bad outcomes (see, Langer and Roth, 1975, Daniel et al., 1998, Gervais and Odean, 2001 and Hirshleifer, 2001). The difference in valuation of losses and gains from the perspective of individuals have led to the examination of the relationship between prior performance and risk-taking behaviour, with researchers reporting diverse results. Consistent with the theory underling the disposition effect[45], literature supports greater risk taking after the experience of losses (Coval and Shumway, 2005, Haigh and List, 2005; Andare and Iyer, 2009), but also after the experience of gains (Ben David et al., 2018).

Ben David et al. (2018) is the first study that empirically examines the self-attribution bias. Using the trading activity of retail investors in FX market, the authors test whether retail investors correctly evaluate their past trading performance and adjust accordingly their risk-taking behavior. Risk taking is proxied with the use of the change in the average/median trade size and documented results are suggesting the existence of self-attribution bias on FX traders, leading to inappropriate increase in risk taking. There is no empirical study that uses demographic characteristics to identify subgroups of investors which are prone to self-attribution bias. There are only experimental studies analyzing the effects of gender on the self-attribution bias typically using students as subjects, while the behavior under examination is other than trading activity. [46] Reported evidence of

[44] See, De Long et al. 1990, Kyle and Wang 1997, Odean, 1998, 1999, Daniel et al. 2001, Barber and Odean, 2000, 2001, 2002, Graham et.al, 2009.
[45] Disposition effect has been developed based on the concept of prospect theory according to which, the magnitude of dissatisfaction when loosing is greater than the magnitude of satisfaction when winning, leading individuals to the acceptance of higher levels of risks in order to avoid losses.
[46] See, paper of Beyer 1990 and references therein.

experimental work, shows that men are more prone to self-attribution bias than women. Therefore, following experimental work findings, we expect that women will be less likely to be prone to self-attribution bias.

Generally, behavioral bias literature supports that biases such as the disposition effect, are shown to be weaker for wealthier and more sophisticated investors with higher trading experience and better employment status (Feng and Seasholes, 2005; Dhar and Zhu, 2006 and Calvet et al., 2009; Seru et al., 2009; Grinblatt et al., 2012). We expect that the characteristics representing those investors will be the characteristics that reduce the probability of exhibition to self-attribution bias. Accordingly, older, educated, employed investors with higher income and net wealth are less likely to be prone to self-attribution bias.

Hypothesis 2: *Men are more prone to self-attribution bias, while older, educated, employed investors with higher income and wealth are less.*

3. Dataset and Descriptive Statistics.

3.1. Dataset

We use a detailed proprietary dataset from a European regulated financial services firm that provides online trading services to retail investors. The dataset contains retail customer trade by trade data, ranging from October 24th, 2014 to February 27th, 2018, for 107 different forex instruments. It contains all trades for 40,453 clients in 49,880 accounts and a total of 21,626,713 trades, 97.41% of which are in currency pairs and Gold. EURUSD topping the list at 32.28% and USDJPY and GBPUSD both at around 11.5% each. Distinct restrictions and circumstances are describing the different forex instruments therefore, we restrict our sample to include the trading activity on standard accounts[47] and investors that execute trades only on currency pairs or gold. A number of investor characteristics are also included in the dataset. Characteristics are separated into demographic characteristics for each trader, like age, gender, educational level, employment status, income, net worth and

[47] Standard accounts allow access to standard lots of forex instruments. 1 lot for currency pairs equals to 100,000 units of the base currency or for gold the dollar value of 100 ounces. No extra commissions are charged on each trade other than the reported spreads.

geographical region but also trade's characteristics like the side of the trade (buy initiated trade vs sell initiated trade), the trade's open and closed date-time, the trade's open and closed price, the trade's volume, the level of leverage, the number of the account, the registration date of each account and the first registration date of each trader. We remove clients with erroneous observations from our original sample, i.e. traders with duplicate: (a) gender; (b) day of birth; (c) continent; (d) educational level; (e) employment status; or age less than 18. In addition, we delete specific observations; (a) opened on weekends (b) zero stated volume; (c) missing volume after the conversion in euro terms due to missing prices at the opening time.

3.2. Descriptive statistics

Our final sample includes 31,906 clients with 37,926 accounts and a total of 11,186,437 trades. Table 1 shows descriptive statistics for the dataset. In Panel A we observe that around 86% of the traders are from Asia and Europe, with Asia dominating at 64.34%. Around 81% are men and 19% are women. The majority of traders, 72.72%, are between 20-40 years old and 57.88% have at least a bachelor's degree (15.15% have postgraduate degrees). Around 85% are employed including 28.28% that are self-employed. The remaining identify themselves as students, not working or retired. 70.96% have an income of less than US$50,000 while 14.40% have an income of more than US$100,000, and 64.05% have net worth less than US$50,000, while 10.73% have net worth of more than US$1 million. Our sample of traders is on average younger[48], with lower average income and net worth, but with comparable education level and gender split when compared with the demographics of other US based stock trading samples used in the literature (see for example Barber and Odean, 2001 and Graham et al., 2009).

Table 1, Panel B, presents descriptive statistics on clients' trading life and trading activity. We define the active trading life for each investor in the sample as the period between her first registration date and the date of her last trade. The median (average) active trading life is 1.68 months (7.26 months) and the median (average) number of trades per month

[48] According to foreign exchange contact group of European Central Bank (ECB), the median age of retail investors in FX market is 35, which is analogous to estimates in our sample (https://www.ecb.europa.eu/paym/groups/pdf/fxcg/2301/Retail_FX.pdf?8b9766f1bbf56797757c4c2cb391f305).

during the active life is 34.27 (87.49 trades). The median time between new trades by an investor is 9.72 hours and the median duration of each trade is 5.18 hours.

3.3. Risk-Taking Measure

Leverage offers another dimension to explore the attitude of investors toward risk which can be captured by the level of leverage they use for their accounts. For the sample period under investigation, forex firms can offer a leverage that can come up to the very high of 1:1000, or even higher. Leverage enables a trader to control a larger amount of capital in a trade using a relatively small amount of his own. It is important to note that the use of leverage magnifies both gains and losses. For example, assume that a trader intends to invest $100 without the use of leverage and opens a trade on EURUSD. If the EURUSD rate moves down 100 pips, let's say from 1.1233 to 1.1133, he would have made $1 loss on a deposit of $100 which is equivalent with a 1% loss of his initial capital. If his selected leverage is 1:100 his $100 investment is now worth $10,000 and the same 100 pips downward movements will result in a $100 loss on a deposit of $100 which is equivalent with a 100% loss of his initial capital. Most of the trades in our sample are highly levered (100 or more), but due to confidentially reasons the exact distribution cannot be revealed.

Beyond the fact that FX market offers the highest leverage level that an investor can obtain in financial markets, a feature used in this study to proxy risk taking behaviour, a trader in FX market has the option to use more than one leverage level at the same time. Thus, to test the existence of relation between demographic factors and risk-taking behavior we construct two alternative risk-taking measures; the equally and the size weighted leverage across each trader's life. Equally weighted leverage is estimated as the average leverage across all trades while size weighted leverage is the average leverage weighted by trade size. For estimating the size weighted leverage all trades are converted in euro money terms.

To test if retail investors adjust their risk-taking behavior based on past performance, we use traders' changes in leverage level. Therefore, we isolate traders that are using two leverage levels at the same time and this leaves us with to 754 traders, with 2,173 accounts and 813,277 trades. Table 2 reports descriptive statistics for the number of switches and the time it takes to switch. A switch is defined as the point at which a client moves from one leverage level to another. For example, he may start trading using a leverage of 50

(1:50) and then carry on trading using a leverage of 100 (1:100). The point at which he moves from a leverage of 50 to a leverage of 100 is defined as a switch. From the 754 traders, the median (average) number of switches is 3 (55.2). 41,589 switches are included[49] and it takes a median time of up to 27 minutes to switch. By splitting the sample into the time up to the first switch and the time from the second switch onwards we observe that the median time up to the first switch is 60,498 minutes (equals to 42 days) while the median time from the second switch onwards is only 25 minutes. Consequently, we observe that it takes too long for investors to switch for the first time but thereafter the switches occur more frequently.

4. Empirical Analysis

The project investigates the risk-taking behavior of retail investors by examining whether demographic factors differentiate the level of their risk-taking and the way they adjust their risk taking behavior based on past performance. This section describes the methodology used along with the empirical results.

4.1. Relationship between retail investors risk taking behavior and demographic factors.

To examine the first part of our research question we conduct cross-sectional regression analysis for our sample of 31,906 traders. As mention in section 3.3, a trader in FX market has the option to use more than one leverage level at the same time. Thus, in order to cross sectionally test the existence of the relation between demographic factors and risk-taking behavior we construct the size weighted leverage across each trader trading life. Size weighted leverage is estimated as the average leverage weighted by trade size and in our regression analysis, is used as the dependent variable. As independent variables a variety of demographic characteristics, like age, gender, educational and employment status, income, wealth and geographical region are included.

Table 3 the reports results from the cross-sectional regression analysis with robust standard errors. Observing the first two columns, which display the coefficients and t

[49] Switches are equally distributed. 20764 switches (49.93%) refer to a decrease on leverage level and 20,825 (50.07%) refer to an increase. 49.20% of those traders start trading using their high level of leverage while 50.80% start trading using their low level of leverage.

statistics when we include one category at a time, we can see that all demographic characteristics are found to significantly affect the risk-taking levels of individuals. Consistent with our first hypothesis, more educated (coefficient of BSc=14.48 and MSc= 16.09) and employed traders (coefficient of Employed= 18.71 and Self-Employed= 12.12) are willing to accept higher level of risk. The retired dummy, under the employment category is negative and significant at the 5% level indicating that retired clients are taking up to 27 times less leverage than clients who are considered as students; an outcome align with the idea that older investors exhibit lower risk tolerance levels than young investors. Observed effect is also grabbed by the negative and significant effect of age where, one-year increase on age translates to 0.35 times lower leverage or in other words a 65-year-old individual has a leverage difference with a 20-year-old individual of -15.75. The dummy variables considering the continent of residence over the base case in which the trader is defined as an Asian, are negative and significant implying that, as predicted, traders from Asia generally engage in higher risk levels and the coefficients are showing that they are followed by Africans, Europeans, Americans and finally traders from Oceania. Results concerning the income and the net worth reveal that traders with an income of more than 100 thousand a year and net worth of more 1 million in total, are willing to accept higher levels of risk with the overall net worth results to be mixed. In particular, while traders with more than 1 million are willing to accept more risk than traders with net worth less than 50 thousand, on the other hand, traders with net worth ranging from 100 to 500 thousand, 500 to 1ml thousand are willing to accept less. What was unexpected, is the negatively significant coefficient (at the 1% level) of gender variable, suggesting that women generally engage in higher level of risk than men.

All results, except of age, are qualitatively and quantitatively the same when we include different combinations of variables. Insignificance of age variable, in all combinational models, is indicating that other demographics are responsible for changes in the effects of age on risk taking rather than the age itself. The unexpected gender difference spotted in all regressions specifications is a first indication that women in FX market are significantly different from women in equity markets. By including in our model Client's Life Month variable[50], which captures the experience of each investor and interact it with gender

[50] Clients life month variable is measured as the monthly difference between the date of each client's last open trade and their first registration date.

(Model 6), we observed that as male investors gain experience, they increase their risk tolerance levels but with the overall effect on males to be lower than the overall effect on females (-34.35+14.73=-19.62)[51].

4.1.1. Robustness test for the risk taking of women versus men

As a robustness test for the unexpected result about the risk taking behavior of women, we further implement propensity score matching method, according to which each woman in our sample is matched with a man, based on demographics, without the use of replacement and a caliper[52] of 0.1. To check whether the propensity score match enable us to balance effectively the women versus men samples, we run a logit regression analysis for the 12,300 investors (6,150 women along with 6,150 matched men), which use Women as a dependent variable and demographic characteristics as independent. Women is a dummy variable equal to one if the trader is women and zero otherwise. As observed in Model 1 in Table 4, we manage to obtain groups with similar explanatory variables since none of them is found significant.

Consequently, to verify that women are associated with higher levels of risk taking even when comparing them with men with similar demographics, we reemployed regressions of table 3, according to which the dependent variable is the size weighted leverage and demographic characteristics are the independent variables. Indeed, the result remain consistent, with women to be willing to trade on higher levels of leverage than men by approximately 27 units in model 2 and 35 in model 3. In Model 3, we observed again, that as male investors gain experience, they increase their risk tolerance levels but with the overall effect on males again, to be lower than the overall effect on females (-35.12+15.41=-20.71).

4.2. Do retail investors adjust their risk-taking behavior based on their past performance?

Expanding the analysis on the risk attitude of individual investors, in this section, we examine how retailers are choosing to adjust their risk-taking behavior based on their past

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[51] The results remain unchanged when we use size weighted leverage as an alternative measure. Equally weighted leverage is estimated as the average leverage across all trades. Results are reported in appendix.
[52] Caliper is the maximum allowable distance between propensity scores used for matching.

performance. Since we use leverage level to proxy for risk taking, in order to test whether the aforementioned statement is valid we need to isolate traders who are adopting more than one leverage level in the same time, in a sense to be able to alter their risk taking behavior. As mentioned in section 3.3. there are 754 traders who are concurrently using different leverage levels, thereby as a first step, before investigating how past performance affect adjustments on risk taking behavior, we examine who are those traders and whether they are different from those they don't.

4.2.1. Who are choosing to adjust their risk-taking behaviour?

To examine which demographic characteristics are affecting the likelihood of trader adopting more than one leverage level at the same time, we turn to logit regression analysis, in which all 31,906 traders are involved. The dependent variable is an indicator that takes the value of one if a trader uses more than one leverage level and zero otherwise whereas the set of independent variables contains all demographic characteristics included in our sample (age, gender, continent, educational and employment status, income and wealth). We also control for clients' trading life (*Clients Life Months*) since we have seen that an average investor remains active for almost 7 months and it takes on average 75 days (almost 2.5 months) to change leverage level for the first time and in addition we control for the number of distinct symbols used through investor's trading life (*Distinct Symbols*) as different leverage level may be used by each investor to capture differences in information or confidence regarding specific instruments.

Results are reported in Table 5 with the first three columns displaying the logit regression outcomes (estimates, z-statistics and marginal effects) when we include one category of each demographic at a time while the rest of the columns present results for a combination of them. Overall, we observe a statistically significant effect on demographics; however by observing their marginal effects, none of them appear to be economically significant.

4.2.2. How do demographics differentiate the way that past performance affect retail investors' risk taking behavior?

To examine whether demographic factors differentiate the way that past performance affect retail investors' risk taking behavior, we concentrate on the 754 traders that are using two different leverage levels at the same time. Motivated by our early unexpected finding according to which women found to be willing to accept higher levels of risk than men do, we select gender to be the first demographic under examination. The 99th percentile level for the number of switches of women equals to 520 and 720 for men. To avoid our results to be affected by the behavior of clients that executed an extreme number of switches we remove from our sample those with more than 520 switches throughout their trading life time. Therefore, we end up with 744 clients, from who 119 are women and 625 are men. Women (men) execute a total of 6,103 (36,214) switches with 3,055 (18,128) referring to a change towards their high level of leverage and 3,048 (18,086) towards their low level.

After identifying our sample, we perform logit regression analysis which considers as a dependent variable an indicator that takes the value of one if the transaction of a corresponding trader is executed on its high leverage level and zero otherwise. To capture the effects of past performance for each investor, we use the information included in the five most recent trades within a week and construct two different measures. The first is a continuous variable which measures the size weighted average return, *Wght Rtn* and the second is a dummy variable indicating whether the size weighted average return is positive, *Pos Wght Rtn*. To test if investors adjust their risk-taking behaviour, we need to define the point at which the risk level of a trader changes, in our case the leverage level. Thus, a *Switch* is defined as the point at which a client moves from one leverage level to another and is an indicator that equates to one at that particular point. To examine our second research question, that is whether retail investors risk taking behavior is adjusted based on past performance, interactions among switch and past performance variables are created. In all regressions we control for the trades occurring up to the first switch[53] as well as for the trader, the day of the week and the calendar week.

4.2.2.1. Does gender differentiate the risk taking behavior?

As a first step, we run the logit regression described above separately for men and women with the direct logit regression results to be reported in Panel A of Table 7 and the models' corresponding predicted probabilities for switching to the high leverage level to be presented in Panel B of Table 7. , Men and women outcomes are reported in both panels

[53] This is a dummy variable that takes the value of one if a trade is referring to the period before the first switch. As shown in section 3.3., time up to the first switch is much higher compared to rest of switches.

(A and B) in columns 1 and 2 respectively. Additionally, in order to exam whether differences in behavior are arising from differences of gender per se, we use a logit regression of *Women* on demographic characteristics and implement 1:1 propensity score matching method, with which each woman in our sample is matched with a man, without the use of replacement and a caliper of 0.1[54]. Therefore, we manage to identify a control sample of men for 117 women out of 119. Column 3 (Panel A and B) reports the results about the behavior of the control group, called psm men, while column 4 (Panel A and B) presents the results for the behavior of the non psm men and that is the behavior of all men excluding the psm one (508=625-117). Columns 5 and 6 report analogous results of columns 3 and 4 when using 1:2 propensity score matching method and those are the outcomes for the behavior of 229 psm men and 396 (625-229) non psm Men. Table 6 shows that both propensity score matching methods, 1:1 and 1:2, enable us to balance effectively the women versus men samples, since when running a logit regression of Women on demographic characteristics, using the 117 women and their control sample of men, 117 in Model1 and 229 in Model 2, none of the explanatory variables is found to be significant.

At a first glance, we can see some statistically significant differences between the trading behavior of men and women (columns 1 and 2) which somehow disappear when we compare the behavior of women (column 2) with the behavior of the control sample of men (column 3). More specifically, predicted probabilities for switching to the high leverage level on Table 7 Panel B, show that when men switched, as gains increase, they tend to increase their exposure to risk when past returns are positive, while when past returns are negative their risk taking behavior remains unchanged. For example, as past weighted average return moves from 0 to 5%, the probability of switching to a higher level of leverage moves from 54.40% to 83.96% with most of the differences between the probabilities to be statistically significant,[55] whereas at the same time, as past weighted average return moves from 0 to -4% the probabilities moves from 53.08% to 66.18% with the differences between the probabilities not to be significant. This behavior is consistent with the notion that men exhibit self-attribution, as by increasing their exposure to risk with the increase

[54] Results are qualitatively the same when we also control for the trader's level of risk (equally weighted leverage level) and trading life (client's life in months) in propensity score matching method or use a caliper of 0.01.

[55] e.g. moving from 4% to 5%, the probability of switching to a higher level of leverage increases from 79.47% to 84.96%, a significant change at the 5% level.

on gains they accredit successful trading to their own skills and blame external factors, such as bad luck for unsuccessful outcomes since the probability of using their high level of leverage remains unchanged with higher levels of losses (an analogous behavior to the increase on leverage level as gains increase would be the decrease on leverage level as losses increase). As expected, women on the other hand are not prone to self-attribution bias. In detail, women decrease their exposure to risk as losses and gains increases although the differences are not overall statistically significant. Interestingly, the same pattern is observed for the control sample of men. When we remove from the whole sample of men the control sample (column 4), the self-attribution bias effect turns out to be even stronger. In particular, non psm traders are becoming more risk seeking after the increase of both, gains and losses. The increase of risk taking in the domain of losses does indeed makes the self-attribution effect more robust as with the increase on their risk exposure after losses it becomes more obvious that they blame external factors for bad outcomes but then again, this behavior is consistent with the behavior of a gambler who after losses increases the size of the bet with the hope to recover all previous sufferers.

So, the first impression that men exhibit self-attribution bias while women are not, is diminished after matching women with men based on their demographic characteristics and compare the two samples. We verify further the documented outcome by using the 1:2 propensity score matching method and increase the control sample of 117 men to 229. The new controlled sample still, cannot be characterized by the exhibition of self-attribution bias. We observe that in the domain of negative weighted average returns, controlled men display the same behavior as women but in the positive domain a reverse behavior is spotted even though margins and differences between them are not statistically significant. In contrast, the self-attribution bias effect intensifies for the 396 non psm men, with all differences, for positive and negative past returns, being statistically significant[56].

4.2.2.2. How do other demographics differentiate the exhibition of self-attribution bias?

In the analysis of section 4.2.2.1, with the use of demographic characteristics, we identify for the sample of women, a control sample of men and show that gender per se does not

[56] Results are robust when we further control for the time of the day or the corresponding symbol for each trade. Furthermore, to capture the behavior of traders that switched more than once, since a onetime change is more likely to be driven by financial stress response, we rerun regressions for the subsamples of traders who execute two switches and above. Results are qualitatively the same.

determine the exhibition of self-attribution bias. Observed outcome is valid when we double the number of participants in the control sample. Therefore, we end up with two samples; one which includes all women and the 1:2 control sample of men, with the specific sample to be clear from the effects of self-attribution bias[57] and another with the rest of the traders who are prone to the bias. In this section, we use those two samples to test which demographics differentiate the presence of the bias.

Table 8 presents outcomes of logit regression which uses as dependent variable an indicator that takes value equal to one if a trader belongs to the sample which is prone to self-attribution and zero otherwise. The first three columns report the logit regression outcomes (estimates, z-statistics and marginal effects) when we include one category of each demographic at a time and the rest display outcomes from regressions when using a combination of them. Besides the impact of education, consistent with our second hypothesis, evidence reveal that sophisticated investors are less prone to the bias and the effects appear to be also economically significant. In particular, we observe that older, employed, highly paid, and wealthier investors are less likely to exhibit self-attribution bias. For instance, employed or self employed investors are up to 30% less likely to exhibit self-attribution bias while the probability of decrement for highly paid and wealthy investors can reach up to 8% and 30% respectively. A one-year increase on age lead to 1% reduction in the probability of exhibition of self-attribution bias, which is equivalent to 10% reduction on the probability with 10 years increase on age, 20% with 20 years, 30% with 30 and so on. The significant magnitude of this effect can be also captured by the documented 66% negative probability on the retired dummy for the employment category. Regarding the impact of continent of residence, we find that Europeans are most likely to be prone to the bias followed by Africans Americans and finally traders from Asia. Results are qualitatively the same across all regressions specifications.

4.2.2.3. Robustness test for the determination of self-attribution bias.

Does the way that past performance affects the risk adjusted behavior of retail investors indeed corresponds to self-attribution bias effects? One could conjecture that changes in risk taking levels does not necessarily suggest the exhibition of the bias itself but instead

[57] With the use of 1:3 propensity score matching method the self-attribution bias effect on the non psm group becomes weaker indicating that men with self-attribution bias are transferring on the control sample of men.

they reflect the ability of investors to properly analyse past performance indications or even reflect responses to the acquisition of credible information. If the first scenario is valid, as Ben-David et. al. (2018) also supported, we expect to observe that the same pattern that descripts the relationship between changes in risk level and past performance to likewise apply between current performance and past performance. At the same time, if the second scenario is valid, we expect to detect that higher levels of risk are predicting higher contemporaneous returns.

To address these concerns, we employ two different regression specifications. For tackling the first one we make use of the logit regression described in section 4.2.2.1 but instead of including as dependent variable the indicator that takes the value of one if the corresponding trade refers to the traders' high or low level of leverage, we use their current level of performance. Current performance is estimated as the log difference between the closed spot price minus the open spot price of the current trade. Results are reported in table 9. To alleviate concerns about the second scenario we also employ OLS regression analysis on which the depended variable is the current performance for each trade but as independent variable we include the interaction term of Switch variable with a dummy which specifies whether the corresponding trade of each trader is occurring using the high or the low level of leverage. Outcomes for the second specification are reported in table 10.

Table 9 demonstrate that not only we do not observe the same pattern between current and past performance as the one noted between changes in level of risk and past performance but more precisely there is no significant correlation between the two, rejecting the hypothesis that changes in risk taking behavior reflect the correct response of traders on past performance. In addition, Table 10, reject also the hypothesis that changes in risk may refer to responses to credible information since again is not just that we do not spot a positive relation but instead, there is no association between returns and switches to a higher or a lower level of leverage. Therefore. We alleviate concerns about alternative interpretation for results demonstrating the existence of self-attribution bias. In addition, in both tables we are controlling for *Trade's Duration* and overall there is a documented robust, negative relationship between the time that a trade remains open and current performance, meaning that as the holding period of a trade increases the return for the corresponding trade decreases. This result could be an indication of individuals investors being prone to the disposition effect as the literature suggests, even though in our models there is no distinction between losing and winning trades.

5. Conclusions

The magnitude of the effects resulting from a financial decision making are directly related to risk taking behaviour. Even if measuring financial risk taking is crucial, in practice there is a difficulty with its empirical investigation due to the subjective nature of risk taking and the variation in the techniques used to examine this phenomenon.

One of our study's key innovations is the use of leverage level, a widely used mechanism in forex market to obtain a direct dimension and explore investors' attitude toward risk. More precisely, we examine whether demographic factors such as age, gender, educational level, employment status, income, net worth and geographical region, differentiate investors willingness to accept risk as well as the way that past performance affects adjustments to their risk taking behavior.

Using an up to date dataset, from October 24th, 2014 to February 27th, 2018, for 31,906 individuals who account a total of 11,186,437 trades on currency pairs and gold, we find that that consistent with existing literature, young, educated investors, with higher employment status and very high income and net worth are willing to accept higher levels of risk. Results about the continent of residence are proving that Asian traders are generally engaged in greater risk levels, followed by Africans, Europeans, Americans and finally traders from Oceania. Against to our expectations, women appear to engage in higher levels of risk than men do, implying that females in FX market are significantly different from females in equity markets.

Motivated by our unexpected result about the risk taking behavior of women, we extent our investigation on the risk attitude of individual investors by examining how retailers adjust their risk-taking behavior based on past performance, selecting gender to be the first demographic under examination. At first, we provide evidence consistent with the idea that men exhibit self-attribution bias. Self-attribution bias is defined as the tendency of people to recognise own skill abilities for success while blame external factors for unfavourable outcomes. We support the exhibition of the bias through the observation of an increase on risk taking level, the leverage level, after the experience of gains whereas after the experience of losses the probability of switching to a higher level of leverage remains unchanged (instead of reducing) or even increasing. Observed gender behavioural distinction, is diminished after matching women with men based on their demographic characteristics and compare the two samples, suggesting that reported distinction arises mainly from other demographic differences and not gender per se. Thus, we then employ an analysis to identify which demographics are stimulating the presence of self-attribution bias and outcomes reveal that sophisticated investors are less prone to the bias and the effects appear to be economically significant.

Understanding how risk-taking behavior differentiates among retails investors has important implication for retail investors and for financial services planners and investment advisors. Retail investors, knowing how their risk-taking behavior is affected, can avoid misleading risk taking while knowledge of heterogeneous risk-taking behavior formation would be helpful for financial services planners and investment advisors, on the creation of risk-specific financial investment packages.

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Table 1: Summary Statistics for retail investors' characteristics

Panel A: This table presents summary statistics for the demographic information considering the 31,906 retail investors.

Parameter	Frequency	Percent		Frequency	Percent
Gender					
Mr	25755	80.72	Mrs	6151	19.28
Age					
18-20	842	2.64	50-60	2300	7.21
20-30	12370	38.77	60-70	702	2.20
30-40	10832	33.95	70-80	135	0.42
40-50	4704	14.74	80-100+	21	0.07
Education Level					
High School	11622	36.43			
BSc	13632	42.73	Doctorate	507	1.59
MSc	4325	13.56	None of the above	1820	5.70
Employment Status					
Student	2616	8.20			
Employed	17928	56.19	Not working	1665	5.22
Self-employed	9022	28.28	Retired	675	2.12
Income					
LT 50K	22639	70.96			
50K-100K	4674	14.65	MT 100K	4593	14.40
Net Worth					
LT 50K	20436	64.05			
50K-100K	4834	15.15	500K-1M	1295	4.06
100K-500K	1918	6.01	MT 1M	3423	10.73
Continent					
Africa	2825	8.85			
America	1388	4.35	Europe	7053	22.11
Asia	20528	64.34	Oceania	112	0.35

Panel B: This table presents descriptive statistics on clients' trading life and trading activity. It shows descriptive statistics for variables Clients_Life_Month, Clients_Total_Trades, Trades_per_Month, Avg_Time_New_Trade and Avg_Trades_Duration. Clients_Life_Month, indicates clients' trading life in months and is measured as the monthly difference between the date of their last open trade and their first registration date. Their first registration date is given and it could be prior to the starting point of our dataset, October 24th, 2014. Clients_Total_Trades is defined as clients' total trades during their trading life in the sample period. We calculate the Trades_per_Month as the ratio of each client's total trades during their trading life to their trading life in months. For estimating the average time of opening a new trade by client, Avg_Time_New_Trade, we sort our dataset based on the open trades datetime and calculate the difference between each time with its lagged value. We then average those values by client. For estimating average time of holding open positions by client, Avg_Trades_Duration, we calculate the difference between the datetime that each trade opens with its closing datetime. We then average those values by client. Avg_Time_New_Trade and Avg_Trades_Duration are reported in hours.

Variable	Min	P5	P25	P50	P75	P95	Max	Mean	Std Dev
Clients_Life_Month	0	0.03	0.3	1.68	9.53	33.25	70	7.26	11.24
Clients_Total_Trades	1	2	11	45	223	1634	48281	352.37	1168.59
Trades_Per_Month	0	1.03	10.55	34.27	91.25	334.58	7912.9	87.49	181.74
Avg_Time_New_Trade	0	0.28	3.09	9.72	27.96	139.11	13170.62	38.50	179.94
Avg_Trades_Duration	0	0.31	1.90	5.18	14.50	74.83	13536.99	22.19	153.58

Table2: Summary statistics for the number and the time between switches

This table reports descriptive statistics for the number of switches and the time between them. A switch is defined as the point at which a client moves from one leverage level to another. For example, he may start trading using a leverage of 50 (1:50) and then carry on trading using a leverage of 100 (1:100). "Number of Switches per client" indicates how many times the leverage level changes during a trader's trading life. Time up to a switch measures the time it takes to make a switch in minutes (mins) and in days (days). The sample is split into three subsamples, the first includes time between all switches during a trader's trading life (All Switches), the second includes only the time up to the first switch (First Switch) and the third includes times between switches from the second switch onwards (Second Switch Onwards).

Variable		N	Min	P5	P25	P50	P75	P95	Max	Mean	Std Dev
Number of Switches per client		754	1	1	1	3	22	196	5580	55.2	296.3
Time up to a switch											
All Switches	mins	41589	0	0	1	27	223	7296	1255681	4031	28974
	days	41589	0	0	0	0	0	5	872	2.8	20.1
First Switch	mins	754	0	990	16303	60498	144116	369465	1255681	109303	144606
	days	754	0	1	11	42	100	257	872	75.9	100.4
Second Switch Onwards	mins	40835	0	0	1	25	194	4477	612676	2087	16155
	days	40835	0	0	0	0	0	3	426	1.4	11.2

Table 3: Cross-sectional regressions: Link between retail investors risk taking behavior and demographic factors

The table presents estimates of cross-sectional regression models in which dependent variable is the size weighted leverage across each trader's life and is estimated as the average leverage weighted by trade size. The independent variables are defined as follows: Age is the age of the trader in years, Gender is a dummy variable that takes value equal to one if a trader is a male and Client's Life Month indicates clients' trading life in months. A series of dummy variables that take the value of one with respect to each other demographic characteristic is also defined. That is, five dummy variables for Education: BSc, MSc, PhD, None; four for Employment: Employed, Self Employed, Not Working, Retired; two for Income: 50 to 100, MT100; four for Net Worth: 50 to 100, 100 to 500, 500 to 1ml and MT1ml and four for trader's continent: Europe, Africa, America and Oceania respectively; High School, Student, and LT50 for Income, Net Worth and Asia are the reference categories for each corresponding variable. t -statistics are based on robust standard errors. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

		One Category at a time		Multivariate Regressions											
		Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Variables				Model 1		Model 2		Model 2		Model 3		Model 3		Model 6	
Continent	Europe	-65.37***	(-16.35)	-67.84***	(-16.40)	-69.39***	(-16.76)	-66.88***	(-16.15)	-62.15***	(-15.41)	-66.80***	(-16.18)	-66.66***	(-15.95)
	Africa	-48.45***	(-8.41)	-47.79***	(-8.20)	-51.27***	(-8.88)	-47.10***	(-8.10)	-43.93***	(-7.58)	-47.09***	(-8.10)	-47.12***	(-8.08)
	America	-74.29***	(-8.88)	-72.92***	(-8.68)	-74.66***	(-8.90)	-69.34***	(-8.25)	-69.17***	(-8.25)	-69.32***	(-8.25)	-69.21***	(-8.22)
	Oceania	-112.47***	(-4.16)	-111.82***	(-4.12)	-114.75***	(-4.22)	-105.68***	(-3.89)	-102.29***	(-3.78)	-105.63***	(-3.89)	-105.28***	(-3.88)
Education	BSc	14.48***	(4.21)	11.22***	(3.27)	12.24***	(3.57)	12.09***	(3.52)			12.06***	(3.52)	12.18***	(3.54)
	MSc	16.09***	(3.24)	32.41***	(6.37)	34.52***	(6.80)	34.15***	(6.71)			34.17***	(6.71)	34.24***	(6.72)
	PhD	10.35	(0.83)	21.75*	(1.75)	22.72*	(1.83)	24.03*	(1.94)			24.11*	(1.95)	24.05*	(1.94)
	None	-8.16	(-1.13)	-4.18	(-0.59)	-4.92	(-0.69)	-3.99	(-0.56)			-3.95	(-0.56)	-3.95	(-0.56)
Employment	Employed	18.71***	(3.22)	15.96***	(2.66)			15.95***	(2.66)	17.15***	(2.86)	16.26***	(2.80)	15.83***	(2.64)
	Self Employed	12.12**	(1.97)	11.66*	(1.83)			12.70**	(1.99)	12.43*	(1.94)	13.06**	(2.12)	12.93**	(2.02)
	Not Working	-9.99	(-1.13)	-4.01	(-0.45)			-4.12	(-0.46)	-8.15	(-0.91)	-3.84	(-0.43)	-3.76	(-0.42)
	Retired	-27.81**	(-2.21)	-17.73	(-1.31)			-16.45	(-1.22)	-18.44	(-1.37)	-15.43	(-1.24)	-16.05	(-1.20)
Income	50 to 100	-5.93	(-1.33)	-8.30*	(-1.86)	-7.53*	(-1.69)							2.84	(0.50)
	MT 100	13.89***	(3.20)	6.04	(1.39)	6.10	(1.41)							-3.46	(-0.45)
Net Worth	50 to 100	0.23	(0.05)					0.22	(0.05)	3.05	(0.69)	0.30	(0.07)	-0.85	(-0.17)
	100 to 500	-46.74***	(-6.67)					-44.09***	(-6.32)	-40.26***	(-5.79)	-43.98***	(-6.33)	-45.01***	(-5.72)
	500 to 1 ml	-20.35**	(-2.51)					-25.28***	(-3.14)	-21.05***	(-2.62)	-25.21***	(-3.13)	-25.58***	(-2.75)
	MT 1 ml	28.67***	(6.00)					18.69***	(3.88)	20.65***	(4.31)	18.69***	(3.88)	21.64**	(2.57)
Age		-0.35**	(-2.44)	-0.05	(-0.31)	0.00	(0.03)	0.03	(0.20)	0.04	(0.25)			0.02	(0.10)
Gender		-29.08***	(-7.80)	-27.97***	(-7.47)			-27.47***	(-7.35)	-27.93***	(-7.47)	-27.52***	(-7.38)	-34.35***	(-7.96)
Client's Life Month														-0.98***	(-2.63)
Client's Life Month * Gender														14.73***	(3.08)
Constant				721.13***	(92.63)	708.36***	(125.67)	717.85***	(92.20)	725.18***	(96.93)	718.64***	(107.53)	723.20***	(90.65)
Observations		31,906		31,906		31,906		31,906		31,906		31,906		31,906	
Adjusted R-squared				0.016		0.014		0.018		0.017		0.018		0.018	

Table 4: Cross-sectional regressions: women versus men and robust test for their risk-taking differences.

The table presents results for regressions after the propensity score matching method using the full sample of women and the control sample of men. Model 1 reports estimates of a logit model in which Women is the dependent variable and Models 2 and 3 report coefficients of OLS regression in which the size weighted leverage is the dependent variable. In all models, demographic characteristics are included as independent variables. Women (Gender) is a dummy variable that takes value equal to one if a trader is a female (male) and zero otherwise, size weighted leverage is the average leverage weighted by trade size, age is the age of the trader in years and Client's Life Month indicates clients' trading life in months. A series of dummy variables that take the value of one with respect to each other demographic characteristic is also defined. That is, five dummy variables for Education: BSc, MSc, PhD, None; four for Employment: Employed, Self Employed, Not Working, Retired; two for Income: 50 to 100, MT100; four for Net Worth: 50 to 100, 100 to 500, 500 to 1ml and MT1ml and four for trader's continent: Europe, Africa, America and Oceania respectively; High School, Student, and LT50 for Income, Net Worth and Asia are the reference categories for each corresponding variable. z -statistics for model 1 (t-statistics for models 2 and 3) are based on robust standard errors. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

		Logit Regression		OLS Regressions			
		Coefficients	z-stat	Coefficients	t-stat	Coefficients	t-stat
Variables		Model 1		Model 2		Model 3	
Continent	Europe	0.013	(0.27)	-54.43***	(-8.17)	-54.84***	(-8.18)
	Africa	0.051	(0.71)	-32.71***	(-3.23)	-33.59***	(-3.30)
	America	0.005	(0.05)	-68.71***	(-5.09)	-69.79***	(-5.16)
	Oceania	-0.327	(-1.09)	-48.94	(-1.25)	-48.37	(-1.24)
Education	BSc	0.038	(0.93)	11.94**	(2.19)	12.15**	(2.22)
	MSc	-0.011	(-0.19)	34.51***	(4.36)	34.92***	(4.41)
	PhD	0.094	(0.60)	7.11	(0.34)	6.82	(0.33)
	None	0.088	(1.11)	7.57	(0.70)	8.16	(0.75)
Employmen	Employed	0.062	(0.76)	12.86	(1.18)	13.02	(1.20)
	Self Employed	0.037	(0.43)	1.11	(0.10)	1.63	(0.14)
	Not Working	0.040	(0.40)	-5.46	(-0.40)	-4.76	(-0.35)
	Retired	0.077	(0.55)	-38.53**	(-1.98)	-38.42**	(-1.98)
Income	50 to 100	0.019	(0.29)	-6.13	(-0.68)	-6.11	(-0.68)
	MT 100	-0.085	(-0.91)	-0.51	(-0.04)	-0.84	(-0.06)
Net Worth	50 to 100	-0.013	(-0.22)	3.87	(0.47)	4.26	(0.52)
	100 to 500	-0.108	(-1.20)	-52.38***	(-4.02)	-51.96***	(-3.99)
	500 to 1 ml	-0.089	(-0.83)	-26.62*	(-1.77)	-26.05*	(-1.73)
	MT 1 ml	0.000	(0.00)	20.89	(1.48)	20.99	(1.48)
Age		-0.001	(-0.62)	0.26	(1.13)	0.27	(1.18)
Gender				-27.61***	(-5.77)	-35.12***	(-6.25)
Client's Life Month						-0.94**	(-2.51)
Client's Life Month * Gender						15.41***	(2.70)
Constant		-0.017	(-0.19)	711.85***	(57.90)	715.89***	(57.82)
Observations		12,300		12,300		12,300	
Pseudo R2		0.001					
Adjusted R-squared %				0.016		0.017	

Table 5: Logit regressions: Who are choosing to adjust their risk-taking behaviour.

The table presents logit regression estimates where the dependent variable is an indicator that takes the value of one if a trader uses two leverage levels and zero if he uses only one. The sample consists all the 31,906 individuals included in our sample. Demographic characteristics are incorporated as independent variables. Gender is a dummy variable that takes value equal to one if a trader is a female and zero otherwise, age is the age of the trader in years, Client's Life Month indicates clients' trading life in months and Distinct Symbols counts the number of distinct symbols used across each investors trading life. A series of dummy variables that take the value of one with respect to each other demographic characteristic is also defined. That is, five dummy variables for Education: BSc, MSc, PhD, None; four for Employment: Employed, Self Employed, Not Working, Retired; two for Income: 50 to 100, MT100; four for Net Worth: 50 to 100, 100 to 500, 500 to 1ml and MT1ml and four for trader's continent: Europe, Africa, America and Oceania respectively; High School, Student, and LT50 for Income, Net Worth and Asia are the reference categories for each corresponding variable. For each specification the first column reports the estimates of the logit regression, the second he z -statistics calculated based on robust standard errors and the third column reports variables' marginal effects. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

		One Category at a time			Multivariate Regressions					
		Coefficient	z-stat	Marginal effect	Coefficient	z-stat	Marginal effect	Coefficient	z-stat	Marginal effect
Variables					Model 1			Model 2		
Continent	Europe	-0.871***	(-7.49)	-0.0201***	-0.900***	(-7.39)	-0.0207***	-0.579***	(-4.61)	-0.0129***
	Africa	-0.377***	(-2.67)	-0.0087***	-0.378***	(-2.62)	-0.0087***	-0.407***	(-2.73)	-0.0091***
	America	-0.560***	(-2.61)	-0.0129***	-0.566***	(-2.62)	-0.0130***	-0.370*	(-1.69)	-0.0082*
	Oceania	-1.186	(-1.18)	-0.0273	-1.352	(-1.35)	-0.0310	-1.091	(-1.06)	-0.0243
Education	BSc	0.098	(1.17)	0.0023	0.047	(0.55)	0.0011	0.099	(1.13)	0.0022
	MSc	0.149	(1.29)	0.0034	0.269**	(2.27)	0.0062**	0.332***	(2.73)	0.0074***
	PhD	0.483*	(1.95)	0.0111*	0.437*	(1.75)	0.0100*	0.468*	(1.84)	0.0104*
	None	-0.176	(-0.96)	-0.0041	-0.098	(-0.54)	-0.0023	-0.254	(-1.37)	-0.0057
Employment	Employed	0.415***	(2.63)	0.0096***	0.362**	(2.21)	0.0083**	0.368**	(2.21)	0.0082**
	Self Employed	0.264	(1.59)	0.0061	0.190	(1.09)	0.0044	0.309*	(1.73)	0.0069*
	Not Working	0.013	(0.05)	0.0003	0.173	(0.72)	0.0040	0.229	(0.94)	0.0051
	Retired	0.327	(1.11)	0.0075	0.430	(1.36)	0.0099	0.643**	(1.98)	0.0143**
Income	50 to 100	0.491***	(5.08)	0.0113***	0.471***	(3.83)	0.0108***	0.486***	(3.87)	0.0108***
	MT 100	0.635***	(6.86)	0.0146***	0.507***	(3.12)	0.0116***	0.544***	(3.37)	0.0121***
Net Worth	50 to 100	0.260**	(2.51)	0.0060**	0.015	(0.12)	0.0003	-0.078	(-0.62)	-0.0017
	100 to 500	0.347**	(2.36)	0.0080**	0.010	(0.06)	0.0002	-0.084	(-0.48)	-0.0019
	500 to 1 ml	0.390**	(2.27)	0.0090**	-0.095	(-0.49)	-0.0022	-0.103	(-0.52)	-0.0023
	MT 1 ml	0.632***	(6.12)	0.0146***	0.055	(0.31)	0.0013	0.012	(0.07)	0.0003
Age		-0.000	(-0.06)	-0.0000	0.000	(0.03)	0.0000	-0.005	(-1.22)	-0.0001
Gender		0.228**	(2.27)	0.0053**	0.237**	(2.36)	0.0054**	0.013	(0.13)	0.0003
Client's Life Month								0.023***	(8.23)	0.0005***
Distinct Symbols								0.078***	(18.33)	0.0017***
Constant					-4.238***	(-20.49)		-4.963***	(-22.57)	
Observations		31,906			31,906			31,906		
Pseudo R2					0.021			0.093		

Table 6: PSM - Balance effectively the women vs men samples.

The table presents results for logit regressions in which Women is the dependent variable and demographic characteristics are included as the independent variables. Analysis is conducted with the use of the full sample of women and the control sample of men. Women is a dummy variable that takes value equal to one if a trader is a female and zero otherwise. Age is the age of the trader in years while a series of dummy variables that take the value of one with respect to each other demographic characteristic is also defined. That is, five dummy variables for Education: BSc, MSc, PhD, None; four for Employment: Employed, Self Employed, Not Working, Retired; two for Income: 50 to 100, MT100; four for Net Worth: 50 to 100, 100 to 500, 500 to 1ml and MT1ml and four for trader's continent: Europe, Africa, America and Oceania respectively; High School, Student, and LT50 for Income, Net Worth and Asia are the reference categories for each corresponding variable. Model 1 (Model 2) reports results after the 1:1 (1:2) propensity score matching method. z -statistics are reported in parenthesis and are estimated based on robust standard errors. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

		Coefficient	t-stat	Coefficient	t-stat
Variables		Model 1		Model 2	
Continent	Europe	0.967	(1.21)	0.213	(0.41)
	Africa	-0.341	(-0.59)	-0.018	(-0.03)
	America	-0.511	(-0.85)	0.075	(0.13)
Education	BSc	-0.382	(-1.19)	-0.321	(-1.17)
	MSc	-0.378	(-0.91)	-0.119	(-0.35)
	None	-0.045	(-0.07)	0.087	(0.16)
Employment	Employed	0.125	(0.16)	-0.072	(-0.11)
	Self Employed	0.329	(0.41)	-0.054	(-0.08)
	Not Working	-0.239	(-0.23)	-0.156	(-0.17)
	Retired	-0.228	(-0.21)	-0.359	(-0.35)
Income	50 to 100	0.462	(1.00)	0.066	(0.15)
	MT 100	0.823	(1.33)	0.017	(0.03)
Net Worth	50 to 100	-0.448	(-1.08)	-0.052	(-0.13)
	100 to 500	-0.064	(-0.10)	0.213	(0.39)
	500 to 1 ml	-0.443	(-0.62)	-0.291	(-0.47)
	MT 1 ml	-0.358	(-0.56)	0.131	(0.24)
Age		0.003	(0.25)	0.008	(0.60)
Constant		-0.127	(-0.15)	-0.797	(-1.12)
Observations		234		346	
Pseudo R2		0.0273		0.0076	

Table 7: Logit regressions: How past performance affects risk taking behavior.

The table presents logit regression results for which the dependent variable is an indicator that takes the value of one if the trade of a corresponding client is executed on its high leverage level and zero otherwise. The sample consists 744 individuals who are using two levels of leverage at the same time. Past performance's estimates and switch variables are used as independents. Past performance is evaluate using two different measures. The first is a continuous variable which estimates the size weighted average return, Wght Rtn and the second is a dummy variable indicating whether the size weighted average return is positive, Pos Wght Rtn. A Switch is an indicator that takes the value of one at the point at which a client moves from one leverage level to another. Interactions among switch and past performance variables are created in order to capture changes on retail investors' risk-taking behavior. Panel A, reports logit regression estimates with their z -statistics in parentheses estimated based on standard errors and adjusted for heteroskedasticity and clustered at the trader level. Panel B reports the mean predicted probabilities when clients switched to their high level of leverage for different weighted return specifications for each one of the logit regressions presented on Panel A. "Dif" column, displays outcomes for the differences between predicted probabilities when moving from one target-return to another. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

Panel A: Probit Refression Estimates

Variables	All Men	All Women	PSM Men	Non PSM_Men	PSM 1to2 Men	Non PSM 1to2 Men
Switch	-0.54***	-0.29	-0.29	-0.56***	-0.70**	-0.45**
	(-3.22)	(-1.00)	(-1.02)	(-2.91)	(-2.57)	(-2.12)
Pos Wght Rtn	-0.02	-0.09**	-0.02	-0.03	-0.02	-0.02
	(-0.55)	(-2.32)	(-0.52)	(-0.64)	(-0.50)	(-0.42)
Switch* Pos Wght Rtn	0.14	0.36*	0.25	0.09	0.20	0.13
	(1.52)	(1.93)	(0.92)	(0.98)	(0.99)	(1.36)
Wght Rtn	24.80*	11.14	-1.10	31.48*	29.31	20.84
	(1.72)	(0.28)	(-0.04)	(1.94)	(1.35)	(1.15)
Switch * Wght Rtn	-56.12	20.06	70.40	-92.45**	-15.64	-98.41*
	(-1.53)	(0.30)	(1.09)	(-2.01)	(-0.33)	(-1.81)
Pos Wght Rtn * Wght Rtn	-68.74**	5.91	-1.58	-79.90**	-78.98*	-57.27
	(-2.22)	(0.07)	(-0.03)	(-2.20)	(-1.67)	(-1.46)
Switch * Pos Wght Rtn * Wght Rtn	167.49**	-127.87	-129.18	241.82**	88.53	231.63**
	(1.97)	(-0.80)	(-0.62)	(2.50)	(0.53)	(2.25)
Trds bfr Switch	0.30	-1.25*	0.25	0.32	0.13	0.48
	(0.80)	(-1.83)	(0.28)	(0.85)	(0.20)	(1.20)
Constant	-0.79	2.67**	1.75	-1.17	-0.92	-0.77
	(-1.02)	(2.36)	(1.32)	(-1.35)	(-0.48)	(-1.00)
Client	YES	YES	YES	YES	YES	YES
Day_of_the_Week	YES	YES	YES	YES	YES	YES
Calendar_Week	YES	YES	YES	YES	YES	YES
Observations	614,072	112,843	131,969	482,103	240,239	373,833
Pseudo R2	0.506	0.552	0.508	0.523	0.493	0.537

Table 7 (continue)

Panel B: Mean Predicted Probabilities when clients Switch to their high level of leverage												
Range of Returns	All Men	Dif	All Women	Dif	PSM Men	Dif	Non PSM_Men	Dif	PSM 1to2 Men	Dif	Non PSM 1to2 Men	Dif
(5) -0.04	0.6618***						0.7612***				0.8065***	
	(0.0000)						(0.0000)				(0.0000)	
(4) -0.03	0.6308***	(4-5)	0.4278***		0.3298**		0.7120***	(4-5)**	0.4721***		0.7511***	(4-5)***
	(0.0000)	(0.256)	(0.0038)		(0.0189)		(0.0000)	(0.023)	(0.0007)		(0.0000)	(0.000)
(3) -0.02	0.5985***	(3-4)	0.4590***	(3-4)	0.3929***	(3-4)*	0.6579***	(3-4)*	0.4880***	(3-4)	0.6867***	(3-4)**
	(0.0000)	(0.287)	(0.0000)	(0.558)	(0.0003)	(0.062)	(0.0000)	(0.059)	(0.0000)	(0.751)	(0.0000)	(0.022)
(2) -0.01	0.5651***	(2-3)	0.4902***	(2-3)	0.4643***	(2-3)	0.5990***	(2-3)*	0.5039***	(2-3)	0.6148***	(2-3)*
	(0.0000)	(0.31)	(0.0000)	(0.567)	(0.0000)	(0.181)	(0.0000)	(0.095)	(0.0000)	(0.752)	(0.0000)	(0.067)
(1) 0	0.5308***	(1-2)	0.5212***	(1-2)	0.5396***	(1-2)	0.5358***	(1-2)	0.5197***	(1-2)	0.5376***	(1-2)
	(0.0000)	(0.327)	(0.0000)	(0.566)	(0.0000)	(0.236)	(0.0000)	(0.126)	(0.0000)	(0.751)	(0.0000)	(0.100)
(1) 0	0.5440***		0.5469***		0.5643***		0.5431***		0.5397***		0.5487***	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
(2) 0.01	0.6159***	(2-1)	0.4568***	(2-1)	0.4972***	(2-1)	0.6447***	(2-1)*	0.5658***	(2-1)	0.6435***	(2-1)*
	(0.0000)	(0.22)	(0.0000)	(0.251)	(0.0021)	(0.717)	(0.0000)	(0.073)	(0.0000)	(0.862)	(0.0000)	(0.084)
(3) 0.02	0.6824***	(3-2)	0.3677**	(3-2)	0.4316	(3-2)	0.7335***	(3-2)**	0.5914**	(3-2)	0.7286***	(3-2)**
	(0.0000)	(0.1696)	(0.0108)	(0.205)	(0.1899)	(0.698)	(0.0000)	(0.03)	(0.0282)	(0.852)	(0.0000)	(0.038)
(4) 0.03	0.7422***	(4-3)*	0.2869	(4-3)*	0.3707	(4-3)*	0.8085***	(4-3)***	0.6163	(4-3)	0.8006***	(4-3)***
	(0.0000)	(0.097)	(0.1297)	(0.077)	(0.4161)	(0.632)	(0.0000)	(0.001)	(0.1264)	(0.853)	(0.0000)	(0.001)
(5) 0.04	0.7947***	(5-4)**			0.3172	(5-4)**			0.6404	(5-4)		
	(0.0000)	(0.021)			(0.5461)	(0.444)			(0.2249)	(0.847)		
(6) 0.05	0.8396***	(6-5)*			0.2724	(6-5)***			0.6638	(6-5)		
	(0.0000)	(0.092)			(0.6152)	(0.009)			(0.3015)	(0.839)		
Observations	614,072		112,843		131,969		482,103		240,239		373,833	

Table 8: Logit regressions: How demographics differentiate the exhibition of self-attribution bias.

The table presents logit regression estimates where the dependent variable is an indicator that takes the value of one if a trader belongs to the sample which is prone to self-attribution bias and zero otherwise. Demographic characteristics are included as independent variables. Age is the age of the trader in years while a series of dummy variables that take the value of one with respect to each other demographic characteristic is also defined. That is, five dummy variables for Education: BSc, MSc, PhD, None; four for Employment: Employed, Self Employed, Not Working, Retired; two for Income: 50 to 100, MT100; four for Net Worth: 50 to 100, 100 to 500, 500 to 1ml and MT1ml and four for trader's continent: Europe, Africa, America and Oceania respectively; High School, Student, and LT50 for Income, Net Worth and Asia are the reference categories for each corresponding variable. The first three columns report results when including one category of demographics at a time while the other specifications are included demographics in combination. For each specification the first column reports the estimates of the logit regression, the second column the z - statistics calculated based on robust standard errors and the third column reports variables' marginal effects. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

		One Category at a time			Multivariate Regressions											
		Coefficient	z-stat	Marg. eff	Coefficient	z-stat	Marg. eff	Coefficient	z-stat	Marg. eff	Coefficient	z-stat	Marg. effc	Coefficient	z-stat	Marg. eff
Variables						Model 1			Model 2			Model 3			Model 4	
Continent	Europe	1.30***	(4.65)	0.31***	1.72***	(5.10)	0.36***	2.00***	(5.71)	0.42***	1.81***	(4.87)	0.38***	2.08***	(5.61)	0.40***
	Africa	0.70**	(2.37)	0.17**	0.96***	(2.82)	0.20***	0.66*	(1.88)	0.14*	0.92***	(2.75)	0.19***	1.02***	(2.75)	0.20***
	America	-0.53	(-1.17)	-0.13	-0.54	(-1.12)	-0.11	-0.86*	(-1.93)	-0.18*	-0.48	(-1.05)	-0.10	-0.61	(-1.27)	-0.12
Education	BSc	0.57***	(3.37)	0.14***	0.58***	(3.18)	0.12***	0.64***	(3.53)	0.13***				0.66***	(3.52)	0.13***
	MSc	-0.21	(-0.89)	-0.05	-0.42	(-1.59)	-0.09	-0.34	(-1.31)	-0.07				-0.30	(-1.07)	-0.06
	None	-0.77*	(-1.95)	-0.19**	-0.36	(-0.75)	-0.07	-0.76*	(-1.73)	-0.16*				-0.39	(-0.88)	-0.08
Employment	Employed	-0.63*	(-1.80)	-0.15*	-0.63*	(-1.68)	-0.13*				0.07	(0.19)	0.01	0.01	(0.03)	0.00
	Self Employed	-1.28***	(-3.47)	-0.30***	-1.41***	(-3.59)	-0.30***				-0.68*	(-1.76)	-0.14*	-0.82**	(-2.01)	-0.16**
	Not Working	-1.73***	(-3.27)	-0.41***	-1.88***	(-3.16)	-0.39***				-1.40**	(-2.48)	-0.29**	-1.30**	(-2.18)	-0.25**
	Retired	-2.77***	(-3.32)	-0.66***	-2.92***	(-3.80)	-0.61***				-1.10	(-1.23)	-0.23	-1.00	(-1.05)	-0.19
Income	50 to 100	-0.34*	(-1.77)	-0.08*				-0.32	(-1.53)	-0.07				0.69**	(2.04)	0.13**
	MT 100	-0.19	(-1.05)	-0.05				-0.16	(-0.78)	-0.03				1.25***	(2.96)	0.24***
Net Worth	50 to 100	-0.64***	(-3.06)	-0.16***	-0.72***	(-3.18)	-0.15***				-0.60***	(-2.59)	-0.12***	-1.14***	(-3.48)	-0.22***
	100 to 500	-0.33	(-1.12)	-0.08	-0.37	(-1.13)	-0.08				-0.26	(-0.79)	-0.05	-0.78*	(-1.89)	-0.15*
	500 to 1 ml	-1.23***	(-3.27)	-0.30***	-1.58***	(-3.41)	-0.33***				-1.41***	(-3.27)	-0.29***	-2.43***	(-4.28)	-0.47***
	MT 1 ml	-0.50**	(-2.45)	-0.12**	-0.71***	(-3.12)	-0.15***				-0.58***	(-2.68)	-0.12***	-1.84***	(-4.05)	-0.36***
Age		-0.05***	(-6.08)	-0.01***				-0.07***	(-7.25)	-0.01***	-0.06***	(-5.84)	-0.01***	-0.06***	(-6.30)	-0.01***
Constant					0.89**	(2.31)		2.01***	(5.87)		2.40***	(5.80)		2.27***	(5.12)	
Observations		742			724			724			724			724		
Pseudo R2					0.126			0.127			0.132			0.178		

Table 9: Robustness test for the determination of self-attribution bias – Properly analyse past performance

The table presents OLS regression results for which the dependent variable is the current level of performance. Current level of performance is estimated as the log difference between the closed spot price minus the open spot price of the current trade. The sample consists 744 individuals who are using two levels of leverage at the same time. Past performance's estimates and switch variable are used as the main independents. Past performance is evaluate using two different measures. The first is a continuous variable estimated as the size weighted average return, Wght Rtn and the second is a dummy variable indicating whether the size weighted average return is positive, Pos Wght Rtn. A Switch is an indicator that takes the value of one at the point at which a client moves from one leverage level to another. Interactions among switch and past performance variables are created in order to capture changes on retail investors' risk-taking behavior. Trades before Switch and trade's duration are also included as control variables. Trades before Switch is an indicator equals to one for all trades occurred before the first switch while Trade's Duration is the hourly difference between the time that each trade opens with its corresponding closing time. t -statistics are reported in parentheses and are estimated based on standard errors adjusted for heteroskedasticity and clustered at the trader level. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

Variables	All Men	All Women	PSM Men	Non PSM_Men	PSM 1to2 Men	Non PSM 1to2 Men
Switch	-0.005	0.028**	0.003	-0.002	-0.004	-0.001
	(-0.53)	(2.25)	(0.22)	(-0.22)	(-0.36)	(-0.12)
Pos Wght Rtn	-0.000	-0.000	-0.004	0.002	-0.006**	0.005
	(-0.14)	(-0.06)	(-1.57)	(0.43)	(-2.56)	(1.00)
Switch* Pos Wght Rtn	0.023**	-0.030	0.006	0.019*	0.016	0.016
	(2.41)	(-1.58)	(0.41)	(1.77)	(1.13)	(1.33)
Wght Rtn	-5.464	-0.862	-1.351	-6.514	-0.187	-8.530
	(-1.57)	(-0.38)	(-0.75)	(-1.52)	(-0.09)	(-1.63)
Switch * Wght Rtn	-0.984	10.292*	4.275	-1.358	4.961	-3.623
	(-0.19)	(1.87)	(0.86)	(-0.22)	(0.97)	(-0.54)
Pos Wght Rtn * Wght Rtn	8.875*	0.116	3.731	9.420	3.919	10.461
	(1.76)	(0.01)	(0.90)	(1.53)	(0.97)	(1.39)
Switch * Pos Wght Rtn * Wght Rtn	-15.872*	-7.011	-15.127	-11.773	-19.345	-7.734
	(-1.66)	(-0.80)	(-1.22)	(-1.11)	(-1.65)	(-0.64)
Trades before Switch	0.009*	0.014	0.010**	0.010	0.015***	0.006
	(1.86)	(1.62)	(2.03)	(1.62)	(3.23)	(0.85)
Trade's Duration	-0.001***	-0.001	-0.001*	-0.001***	-0.001***	-0.001***
	(-4.61)	(-1.19)	(-1.81)	(-4.35)	(-3.05)	(-3.78)
Constant	-0.419***	-0.165	-0.167	-0.423***	-0.229**	-0.475***
	(-3.85)	(-0.71)	(-1.25)	(-3.62)	(-2.01)	(-3.38)
Client	YES	YES	YES	YES	YES	YES
Day_of_the_Week	YES	YES	YES	YES	YES	YES
Calendar_Week	YES	YES	YES	YES	YES	YES
Observations	615,090	113,164	244,529	483,119	352,880	374,768
Adjusted R-squared	0.121	0.034	0.040	0.133	0.047	0.152

Table 10: Robustness test for the determination of self-attribution bias – Responses to credible information

The table presents OLS regression results for which the dependent variable is the current level of performance. Performance is estimated as the log difference between the closed spot price minus the open spot price of the current trade. The sample consists 744 individuals who are using two levels of leverage at the same time. Trades High Leverage and Switch variables are used as main independents. Trades High Leverage is an indicator is that takes the value of one if the trade of a corresponding client is executed on its high leverage level and zero otherwise and Switch is again an indicator that takes the value of one at the point at which a client moves from one leverage level to another. Interaction among Trades High Leverage and Switch variable is created in order to capture changes on retail investors' risk-taking behavior. Trades before Switch and trade's duration are also included as control variables. Trades before Switch is an indicator equals to one for all trades occurred before the first switch while Trade's Duration is the hourly difference between the time that each trade opens with its corresponding closing time. t -statistics are reported in parentheses and are estimated based on standard errors adjusted for heteroskedasticity and clustered at the trader level. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

Variables	All Men	All Women	PSM Men	Non PSM_Men	PSM 1to2 Men	Non PSM 1to2 Men
Switch	-0.002	0.001	-0.006	0.000	-0.011	0.003
	(-0.21)	(0.08)	(-0.55)	(0.00)	(-1.34)	(0.27)
Trades High Leverage	-0.003	0.005	-0.001	-0.003	-0.001	-0.006
	(-0.84)	(0.70)	(-0.29)	(-0.81)	(-0.22)	(-1.13)
Switch * Trades High Leverage	0.006	0.002	-0.001	0.009	0.009	0.006
	(0.71)	(0.15)	(-0.11)	(1.01)	(0.93)	(0.51)
Trades before Switch	0.009*	0.014	0.009*	0.010*	0.014***	0.007
	(1.95)	(1.60)	(1.91)	(1.69)	(3.01)	(1.01)
Trade's Duration	-0.001***	-0.001	-0.001*	-0.001***	-0.001***	-0.001***
	(-4.94)	(-1.27)	(-1.93)	(-4.68)	(-3.23)	(-4.10)
Constant	-0.400***	-0.171	-0.170	-0.405***	-0.229**	-0.453***
	(-3.81)	(-0.76)	(-1.31)	(-3.59)	(-2.07)	(-3.35)
Client	YES	YES	YES	YES	YES	YES
Day_of_the_Week	YES	YES	YES	YES	YES	YES
Calendar_Week	YES	YES	YES	YES	YES	YES
Observations	622,270	114,063	246,701	489,018	356,305	379,414
Adjusted R-squared	0.133	0.033	0.041	0.146	0.047	0.168

Chapter 3

Flash Crash. An exogenous determinant of individuals behavior in FX market.

Chapter 3: Flash Crash. An exogenous determinant of individuals behavior in FX market

Abstract

This paper examines whether individuals alter their trading behavior after the experience of an unpredictable and extremely short-lived exogenous shock. We exploit the sterling flash crash episode of October 7th, 2016 along with a unique dataset of individual investor trade by trade data in the foreign exchange (FX) market. We find an asymmetric response of individuals trading volume to the flash crash event, which differs based on the direction of their sterling exposure at the time of the incident. We also show that even an instantaneous exogenous market volatility shock can intensify the exhibition of the disposition effect of individual investors. These findings highlight the importance of a deeper understanding of the determinants of individuals trading attitude in a way to correctly model their behavior and enhance their regulatory protection.

"Developments in learning theory shifted the focus of causal analysis from hypothesized inner determinants to detailed examination of external influences on responsiveness. Human behavior … response patterns, generally attributed to underlying forces, could be induced, eliminated, and reinstated simply by varying external sources of influence."

Albert Bandura, Social Learning Theory, 1977

1. Introduction

On Friday, October 7, 2016, around midnight British Summer Time (BST), parallel to two hours ahead in terms of Eastern European Time (EET), an exogenous 200 standard deviation[58] shock strikes the FX market, with the sterling being depreciated against the US dollar by around 9% in less than a minute and hitting a three-decade historical low[59]. The pound rebounded thereafter and recovered most of its initial loss over the following 10 minutes, closing at the end of the day at a price level of 1.7% lower than the day before. The implications of the shock were not constrained in just the GBPUSD exchange rate pair but instead, were spread to all GBP based currency pairs. In Figure 1 Panel A, we can see the minute-by-minute GPBUSD midpoint prices around the time of the event occurrence while in Figure 1 Panel B, the standard deviation of the minute-by-minute returns over 5-minute intervals for the same time period is presented[60].

In this research project we attempt to assess individuals trading response to the sterling flash crash, on October 7th, 2016 which is an unanticipated, short-lived external shock, without any meaningful effect on fundamentals and evaluate whether such an external source of influences can alter their future trading behavior. Compounding the use of an unpredictable event with a tremendous drop in a remarkably short time period along with the availability of trade by trade data at an extremely fine scale, it is feasible to provide a clear distinction between the reaction of investors without open positions at the time of the crash with investors with open positions and more specifically based on whether their

[58] Using the minute by minute midprices, the estimated average minutely standard deviation over 5-minutes intervals, for the period before the event, equals to 0.000107 and at the time of the event the standard deviation went up to 0.022016.

[59] The last time that the GBPUSD currency pair hit a lower rate was back in 1985, where unlike the slip on October 7 2016, it was about the dollar strengthening rather than pound weakening.

[60] Midpoints are defined using the average of bid and ask quotes as those provided by our proprietary source of individual investors trading data and the graph is similar with the graph obtained by the Bank for International Settlement (BIS), (2017) using the Thomson Reuters midpoints. BIS, (2017) The sterling 'flash event'on 7th October 2016, https://www.bis.org/publ/mktc09.pdf

trade is defined as long or short (losing or winning) with respect to the pound. In addition, considering that the crash occurred on British pound, which features prominently in the list with the most traded currency pairs,[61] enables us to acquire a sufficient number of clients and trades within each group to apply our analysis.

Traditional financial theories of investment decisions are based on the assumption that investors act in a rational manner[62], they have homogeneous expectations[63] and markets are efficient[64]. A standard model would predict no differences in individuals' responses to a release of a new information across separate investors' groups while by relaxing its underlying assumptions[65] and allowing emotions to enter into the investment behavior equation, we would expect to observe a different reaction among investors based on the sign (loss/gain) of the experienced impact at the time of the outburst of the exogenous shock. Prospect theory and loss aversion of Kahneman and Tversky (1979); (1991) were the first studies that emphasize the role of emotions in investment choices and provide a more precise configuration of investment decision making[66].

Endogenous elements of human behavior such as age, gender, educational level, employment status, received income, acquired wealth and marital status have been extensively studied in the finance literature suggesting a significant linkage with investment decisions and trading behavior. For instance, demographic characteristics have been consistently demonstrated to significantly influence individual investors level of diversification, trading frequency, risk-taking, profitability as well as the exhibition of

[61] Based on the BIS (2019) triennial survey, https://www.bis.org/statistics/rpfx19_fx.pdf, GBP is the fourth most traded currency with the GBPUSD currency pair possessing the 9.6% of the total daily turnover and ranking in the third position of the most traded currency pairs while the GBPEUR holds another 2.0% of the total daily turnover. Using our sample, we obtain a similar percentage distribution. The GBPUSD ranks second with a percentage of total trades reaching a level of 11.43% and the EURGBP ranks at the ninth position with a percentage of 1.95%.
[62] Von Neumann–Morgenstern (1944).
[63] Markowitz (1952).
[64] Fama (1970).
[65] A more recently developed literature, so-called Behavioral Finance literature, relaxes investors' rationality assumption and suggests that investors are actually exhibiting irrational behavior and they do not always behave in line with the assumptions made by traditional finance. Behavioral Finance is not a theory that aims to replace traditional financial theories, but it suggests that an inclusion of irrational behavior on our standard economic models will complement our understanding of financial markets formation.
[66] Prospect theory and loss aversion of Kahneman and Tversky, (1979); (1991), along with endowment effect theory of Thaler, (1980), make significant contributions on the development of key components of behavioral finance. Kahneman and Tversky and Thaler, published extensively in the field of finance with Kahneman and Thaler being awarded a Nobel Prize in Economics for their contributions in the field of Behaviour Finance. Kahneman was awarded in 2002 and Thaler in 2017.

different behavioural biases,[67] with the disposition effect being one of the most researched biases. Korniotis and Kumar (2011, 2013), support that cognitive skills of investors may also maintain a key role on the formation of investment decisions and realised performance. More specifically, in their first study, by jointly modelling age and experience, they provide evidence of a negative relation between trading performance and age, with the negative effect of cognitive aging dominating the positive effect of experience. In their second study, the authors use demographic characteristics to empirically measure investors "smartness" and show that "smart" investors outperform "dumb" investors. Moreover, they suggest that heterogeneous groups of investors exhibit different portfolio distortions with the distortions of smart investors to be less likely to reflect behavioural biases. Earlier studies have also shown that characteristics representing smart investors moderate the exhibition of disposition effect. Particularly, the disposition effect has shown to be weaker for wealthier and more sophisticated investors with higher trading experience and better employment status (Feng and Seasholes, 2005; Dhar and Zhu, 2006 and Calvet et al., 2009; Seru et al., 2009).

Personal experience effect in investment decisions and trading behavior is an additional behaviour determinant which is strongly documented by various studies with the underlying drivers of personal experience to be generated either endogenously or exogenously. As an example, the influence of learning by doing type of personal experience, captured either by the length of trading or the frequency of trading, is an endogenous factor noted in the studies of several authors. (Feng and Seasholes, 2005; Dhar and Zhu, 2006; Nicolosi et. al., 2008; Seru et. al., 2010; Korniotis and Kumar, 2011).

Our paper contributes mainly to the literature that exploits the exogenous determinants of personal experience. Related work has concentrated on the analysis of investors behavior after the experience of an external shock like a macroeconomic event, an outbreak of civil violence or a natural disaster such as earthquake, hurricane or tsunami. For example, Malmendier and Nagel (2011) show that the experience of a large macroeconomic event, like the Great Depression, is considerably correlated with people's investment decisions and opinions. Reported results align with the findings of other studies investigating the

[67]See, Barber and Odean (2001); (2002); Ivkovic and Weisbenner (2005); Dhar and Zhu (2006); Graham and Kumar (2006); Goetzmann and Kumar (2008); Graham et.al. (2009); Kumar (2009b); Seasholes and Zhu (2010); Grindblatt and Keloharju (2009); Heimer (2016).

effects of similar events on economic choices (Malmendier et. al., 2011; Cronqvist et. al., 2015 and Schoar and Zuo, 2016, 2017) or the effects of alternative macroeconomic events such as technology bubbles, amendments on the labour market conditions or economy's business cycle peaks and slumps in general (Oyer, 2008; Greenwood and Nagel, 2009; Knüpfer et. al., 2014; Cronqvist et. al., 2015; Schoar and Zuo, 2017). Kim and Lee (2014) and Voors et.al. (2012), use the Korean and Burundi wars respectively to exploit the effects of civil violence on individuals risk attitude, with both studies suggesting the existence of a significant link among the two. The impact of traumatic experiences on future investment behavior has also been investigated with the use of different sorts of natural disasters, supporting a notable influence of investors risk-taking behavior following earthquakes, hurricanes, floods and tsunamis with a lack of consensus on the direction of the effect. (Eckel et. al 2009; Cameron and Shah, 2015; Hanaoka et. al., 2015; Said et. al., 2015; Shi et. al., 2015; Cassar et. al., 2017).

Our contribution to aforementioned literature is threefold. First, we utilise a proprietary record of a trade by trade data on individual investors in foreign exchange (FX) market, provided by a European regulated financial services firm that provides online trading services to retail investors. Existing literature examines the response of investors trading in equity markets. Secondly, unlike pre-examined events, the sterling flash crash is an exogenous dramatic trading experience incident[68], occurred on an extremely short-lived period, with minimal to nonexistent fundamental effect and an immediate influence on investors trading activity. Previous studies observe investors responses after an exogenous dramatic life experience event. And thirdly, the fact that the event cannot be predicted or controlled in any way makes it unlikely for investors to prepare in terms of realized trading positions. The aforesaid event's distinctive characteristics along with the short selling ease representing FX market, enables us to have a clear view on the asymmetric effect which can arise due to the event's occurrence.

In investigating investors asymmetric self-adapting behavior, we split investors into those who do not have any open position at the time of the crash and those who do; more precisely, into those with long (losers) or short (winners) open positions pending at that time. Since the implications of the incident are extended to all GBP based currency pairs

[68] The effects wrought by an earthquake, hurricane, tsunami or even a war cannot be compared in no case with the effects that can be induce by a "simple" drop in prices, which represents our external shock.

and investors may retain more than one open GBP- trade at the same time, we identify all trades performed by each investor at the time of the crash and based on the amount of short and long GBP-volume in their portfolio during the event, we classify them as *Long* or *Short* respectively. We verify that Long and Short investors are demographically the same and by tracking and examining their activity prior to the event we show that there is not a consistent pattern that separates the two groups.

In our first test we examine how the occurrence of the sterling flash crash episode affects the trading volume of a GBP-active individual investor. As an active investor we define the trader who places at least one trade in sterling before the event and at least one after. Our identification strategy involves the implementation of an OLS regression on trade by trade data of individual investors with dependent variable the log volume of each trade in euro terms and a post dummy variable as an independent variable. Post is an indicator that takes the value of one if the trade occurred after the event and zero otherwise. In addition, we use dummy variables to identify traders with a long or short open position at the time of the crash and our empirical results show an asymmetric response in the volume activity of individuals, which differs based on their current trading position at the time of the incident. More precisely, traders with a short position at the time of the crash (winners) appear to increase their trading volume after the incident while traders with a long open position at the time of the crash reduce it. The results are robust across different active investor specifications, while the use of different placebo tests alleviates the concerns of spotting a persistent pattern on investor behavior.

We extent our analysis to include the examination of possible effects of the sterling flash crash episode on the investor disposition effect. The disposition effect refers to the behavioural bias according to which investors tend to sell stocks for which they have unrealized gains and hold stocks for which they have unrealized losses. This bias is a direct application of the prospect theory (Kahneman and Tversky, 1979) and it has been labelled as disposition effect by Shefrin and Statman (1985). Odean (1998) documents the disposition effect on individual investors while Barber et al. (2007) find that among other tested groups (e.g mutual funds), individuals exhibit a stronger disposition effect. Using the Feng and Seasholes (2005) methodology, we employ survival analysis with the use of a Cox proportional hazard model with multiple observations per trade and examine how the sterling flash crash episode influences the individuals' disposition effect. We find that the average investor in our sample exhibits the disposition effect consistent with previous literature in both equity and FX market. We do not observe an asymmetric effect on the investor disposition effect when we consider their trading position at the time of the crash, but we observe an overall increase of the disposition effect in the post event period. The reported increase on the investor disposition effect, confirms the theoretical and empirical support of Hirshleifer (2001) and Kumar (2009a) of exaggeration on investors behavioural biases during periods of high uncertainty. Kumar (2009a) exploits the abovementioned statement in respect to disposition effect by measuring the one-month idiosyncratic volatility of stocks, then he splits estimates into ten decile portfolios and measures the investors' average bias within each portfolio. Our study extents the existing literature by using an exogenous shock on market volatility and investigates FX retail investors behavioural responses. We provide evidence of exhibition of stronger disposition effect even after an instantaneous market uncertainty shock.

We complement our analysis by testing whether the increased volatility generated by the exogenous market shock attracted investors with high risk tolerance. To proxy risk tolerance we use the average leverage amount of all trades executed by each investor before the event happening and to recognise traders who were attracted by the increased volatility, we identify those traders who were active only on non GBP-currencies in the pre event period but placed a GBP position in a short period after, in particular, the first day of the event. We use the first day of the event to identify traders that were attracted by increased volatility, since during that day the volatility was 4 standard deviations higher than the normal. We then implement a logit regression analysis using as dependent variable the indicator that takes the value of one if the investor places a trade the first day of the event and zero otherwise. We use as a control group the active investors in non GBP currencies for our whole sample period and we observe that there is 4% higher probability for investors with high risk tolerance to enter into the GBP market the first day of the event, a probability that rises up to 25% when we define a comparable control group with the implementation of propensity score matching method based on demographic characteristics.

Understanding what drives and what configures individuals trading attitude and self-adapting behavior is of a great importance for supervisory authorities for the optimal formation of investors' regulatory protections.

The rest of this paper is organized as follows. Section 2 introduces the timeline of the flash crash event. Section 3 describes the dataset. Section 4 details the methodology and discusses empirical results and finally Section 5 concludes.

2. Timeline and analysis of the event

On October 7th, 2016 at 02:07:03 (EET), there was a flash crash in pound sterling during which the value of GBPUSD currency pair collapsed by almost 9% in 40 seconds, rebounding thereafter and recovering most of its initial loss over the following 10 minutes. The implications of the shock were not constrained in just the GBPUSD exchange rate pair but instead, were spread to all GBP based currency pairs. The BIS (2017) splits the flash crash into three stages and provides a detailed report analysis on the price movements along with several factors that could result in a crash. Specifically, the break down stages of BIS are described as follows:

Stage 1: At 02:07:03 (EET) on October 7th, 2016, the sterling currency began to depreciate rapidly, with the GBPUSD currency quotations collapsing within eight seconds from 1.2600 to 1.2494 (using Reuters mid-prices). The drop was associated with a large number of sterling selling trades.

Stage 2: At 02:07:15, the GBPUSD exchange rate recorded a fall to 1.2400 dollars per sterling. The quick reduction triggered the Chicago Mercantile Exchange (CME) velocity logic mechanism and halted the FX futures trading for 10 seconds. From that point onwards, several minutes of market instability were followed, resulting in multiple CME halts[69]. During that period, the sterling reached the historical low of 1.1491 dollars (at 02:07:41), restoring part of its initial loss thereafter and carried on trading at levels between 1.20 and 1.22.

Stage 3: At 02:20:00 GBPUSD recovered most of its damage, closing on October 7th at a price level of 1.7% lower than the day before. The reported trading volume, and bid-ask spreads during that day were significantly higher than usual.

[69] At 02:09:29 the FX trading was paused for two minutes, restarting at 02:11:29, with a further interruption at 02:11:57 for another 10 seconds.

The BIS report introduces a series of issues that appear to contribute to the unusual thin market liquidity and the significant selling in sterling, starting from the time of the day. It was midnight in European hours, after the American market closed and at the early opening of the Asian one, a time period where very few and most probably inexperienced market participants were active on the unanticipated abnormal sterling shift[70]. The shift was inflated by the aggressive demand for sterling sells to hedge options and the onset of the executions of automatic stop-loss orders. A Financial Times article, which rendered as a negative information for Britain's future, is believed to have deteriorated the adverse circumstances. More specifically, at 02:07:13 (EET), the Financial Times released an article[71] saying that French President Francois Hollande wanted the UK to suffer from leaving the European Union to discourage other members from exiting as well. The corresponding article was distributed rapidly to social media and is considered to have activated an algorithmic sell signals[72].

3. Data and Sample Design

3.1. Overall Sample

For our analysis we use a detailed proprietary dataset provided by a European regulated financial services firm that provides online trading services to retail investors[73,74]. The dataset contains retail customer trade by trade data, from October 24th, 2014 to March 29th, 2019, on 107 different forex instruments. It includes all trades for 137,882 clients in 172,158 accounts with a total of 55,110,142 trades. Each trade carries a number of inner characteristics which are separated into demographic characteristics for each investor who placed the particular trade, like age, gender, educational level, employment status, income, net worth and geographical region or trade's characteristics like the side of the trade (buy initiated trade vs sell initiated trade), the trade's open and closed date-time, the trade's

[70] As pointed out in a later report of Financial Conduct Authority, FCA, in 2018, large banks and other dealers reduced dramatically their trading activity at the time of the flash crash, https://www.fca.org.uk/insight/new-data-sheds-light-sterling-flash-crash.
[71] https://www.ft.com/content/5f84e4c4-8c17-11e6-8aa5-f79f5696c731.
[72] At the same time market manipulations and fat finger errors are not evidently excluded.
[73] There are approximately five thousand active investors per day. Since it was founded, more than 1.5 million investors from more than 150 countries choose this firm for their active trading. The actual name of the data source cannot be revealed due to a related agreement with the firm.
[74] A small number of studies analyse the trading activity of retail investors in FX market at the trader level. See Ben-David et al. (2018); Heimer (2016); Heimer and Imas (2019); Heimer and Simsek (2019).

open and closed price, the trade's volume, the level of leverage, the number of the account, the registration date of each account and the first registration date of each trader.

Around 98% of the trades are in currency pairs and gold with EURUSD topping the list at 29.6%, USDJPY and GBPUSD both at around 11.5% each, GBPJPY at 8.37% and GOLD at 8.10%. Since distinct restrictions and circumstances are describing the different forex instruments, we restrict our sample to include the trading activity on standard accounts[75] and investors that execute trades only on currency pairs or gold. We further remove clients with erroneous observations from our original sample, i.e. traders with duplicate: (a) gender; (b) day of birth; (c) continent; (d) educational level; (e) employment status; or age less than 18. In addition, we delete specific observations; (a) opened on weekends (b) zero stated volume; (c) missing volume after the conversion in euro terms due to missing prices at the opening time. This reduces our traders to 79,438 with 100,816 accounts and a total of 31,355,811 trades.

Considering that the specific study exploits the effects of the sterling flash crash on October 7th, 2016, on investors trading behavior, we restrict our sample period to span 28 days before to 28 days after the event. That is, from September 9 to November 4, 2016. By allowing a wider window around the event under examination, it is more possible to simultaneously allow the effects of other news hitting the market to mutate or even modify the analysis results. A two-month window can mitigate this problem. Subsequently, we end up with 10,563 investors and a total of 1,368,793 trades. Given that the latest registration account is on May 12, 2016 and on average an FX retail trader remains active for about seven months[76], our sample can be assumed to be described by the trading activity of a set of experienced retail investors.

As can be seen from Table 1, 84.90% are men and 15.10% are women with an overall percentage of traders with at least a bachelor's degree of 81.22%. Around 84% are employed including 25.03% that are self-employed. The remaining identify themselves as students, not working or retired. 74.06% have an income of less than US$50,000 while

[75] Standard accounts allow access to standard lots of forex instruments. 1 lot for currency pairs equals to 100,000 units of the base currency or for gold the dollar value of 100 ounces. No extra commissions are charged on each trade other than the reported spreads.

[76] See chapter 2, Heterogeneous risk taking behavior among retailers and also Ben-David et. al. (2018) who reports a six-month active average trading life.

14.29% have an income of more than US$100,000, and 66.96% have net worth less than US$50,000, while 8.54% have net worth of more than US$1 million. Considering the continent of residence, around 94% of the traders are from Asia, Europe, and Africa with Asia dominating at 73.09%. The traders in our sample are relatively younger[77], with lower average income and net worth, but with comparable education level and gender split when compared with the demographics of other US based stock trading samples used in the literature (see for example Barber and Odean, 2001 and Graham et al., 2009).

Table 2 presents descriptive statistics for the trading activity occurred in our sample period at the trade and the trader level. As noted earlier, the latest account registration is on May 12, 2016, therefore in Panel B of table 2 we observe that the minimum active trading life for each investor is around 5 months, overcoming the standard life expectancy of an FX trader. An important point noted from the descriptive statistics of both panels of table 2, is an early indication of the existence of disposition effect. More precisely, Panel A of Table 2 shows that on average 63%[78] of total trades are winning, leading at the same time on an average, negative return (-0.03%), while at the trader level in Panel B, on average 56% of the trades are winning with a -0.08% average return. One of the possible reasons for the unfavourable average returns even when the amount of successful trades exceeds the amount of unsuccessful ones, could be the reluctance of investors to realize losses in respect to gains. The predetermined statement is the definition of the exhibition of disposition effect and is examined in detail in Section 4.2.

In our analysis we investigate the effect of the October 7th, 2016 flash crash episode on active investors trading volume. As an active investor we define the trader who places at least one trade in sterling 28 days before the event and at least one trade in sterling 28 days after the event. Therefore, we end up with 4,021 clients with a total of 879,417 trades.

3.2. Classify Traders

3.2.1. Procedure of classification

[77] According to foreign exchange contact group of European Central Bank (ECB), the median age of retail investors in FX market is 35, which is analogous to estimates in our sample (https://www.ecb.europa.eu/paym/groups/pdf/fxcg/2301/Retail_FX.pdf?8b9766f1bbf56797757c4c2cb391f305).

[78] Same percentage of winnings is documented in Ben David et. Al (2018) study by analysing a similar sample of FX retail investors.

The sterling flashcrash episode took place on October 7th, 2016 at 02:07:03 (EET). In a period of less than a minute, the British pound plunged by almost 9%, rebounding thereafter and recovering most of its initial loss over the following 10 minutes. A rapid price rebounding which cannot be predicted or controlled by any way, leaves no much space in favour of investors' trading position setup and event's exploitation. The preceding unique features along with the short selling ease representing FX market, enables us to classify traders into three main categories and investigate, if there is any, asymmetric, self-adapting behavior. The general idea is to split investors into those who do not have an open position at the time of the crash and those who do; and more precisely into those with long (losers) or short (winners) open positions pending at that time.

Since the implications of the incident are not constrained on just the GBPUSD exchange rate but are spread to all GBP based currency pairs, in order to classify investors who have open positions during the crash, we identify all trades that are executed in any currency pair which includes GBP and opened before 02:07:03 (EET) on October 7th, 2016 and closed after. Table 3 panel A shows all the instruments traded during our sample period and table 3 panel B presents only the currency pairs that include the GBP.

In addition, one trader may retain more than one open GBP- trade at the same time, therefore we follow two distinct construction procedures to split investors into those with long (losers) or short (winners) open positions at the time of the crash. Specifically, *Net Long* and *Net Short* are estimated using the difference of the total amount of long volume with the total amount of short volume. If the difference is positive the client is defined as having net long position and if it is negative a net short position. The second classification removes the clients with concurrent long and short open positions and define as *Only Long* the clients that have only long open positions and *Only Short* those with only short open positions. Table 4 panel A shows that overall 992 clients retain open positions at the time of the crash, with 720 belonging in the Net Long category and 272 in the Net Short. The same table in panel B shows 596 and 218 clients belonging in the Only Long and Only Short categories respectively.

3.2.2. Is the selection of position at the crash random?

Were the sterling shorters at the time of the crash, consistently shorting the pound and respectively the sterling buyers consistently buying the pound? Starting from May 12, 2016, we calculate the cumulative average daily trade imbalance for the different traders' categories and figure 2 presents the results. Imbalance is estimated as the daily difference between the long and the short volume of each group, divided by the summation of the two. The black solid line on Figure 2, A, depicts the cumulative average daily imbalance of the traders with net short open positions at the time of the crash (winners), the blue long dashed line the traders with net long open positions (losers) and the red short dashed line the rest of the traders in our sample. We observe that there is no consistency between the group categories and the sign of the imbalance. We obtain similar results for the sample with the only short and long open positions at the time of the crash (Figure 2, B). For further examination we measure the correlations between the groups and there is no significant association among the net long (only long) and net short (only short) categories (correlation=0.05 (-0.02) and p-value=0.56 (0.80)), but positive and significant for the rest of the clients (correlation for the rest of the clients with Net Long (Only Long)=0.50 (0.41) and p value=0.00 (0.00)) and with Net short (Only Short)=0.26 (0.21) and p value=0.00 (0.02) . These outcomes provide no indication of any comovement between traders with long and short open positions at the time of the crash but show an overall relation in the trading activity of both with the rest of the clients.

3.2.3. Are traders that retain short and long open positions at the crash demographically different?

To examine whether demographic characteristics are affecting the propensity to retain long or short open positions at the time of the crash, we employ logit regression analysis in which the dependent variable is an indicator equal to one if a trader has a long open positions and zero if it has a short position. Demographic characteristics like age, gender, continent, educational level, employment status, income and net worth are included as independent variables. Logit Regression outcomes are reported in Table 5 with the first three columns (estimates, z-statistics and marginal effects) using the Net Long/Net Short classification of investors and the following three columns the Only Long/Only Short classification. Overall, we observe that except from gender and a subcategory of net worth, our traders are demographically similar. In our empirical analysis we include trader fixed effects to capture any investor-specific characteristic that can affect or determine the trading behavior.

4. Empirical Results

4.1. Flash Crash effect on Trading Volume

4.1.1. Baseline analysis

Our first test, studies how the occurrence of the sterling flash crash episode affected the trading volume of GBP-active individual investors. For our baseline analysis, we use similar model as the one used by Heimer and Simsek (2019) for testing the effects of a leverage constrain on the trading volume of retailers. More specifically, we employ ordinary least square regressions of the following structure:

$$Log(volume)_{it} = b_1 + b_2\ post + b_3\ post{*}long + b_4\ post{*}short + \varepsilon_{it} \quad (1)$$

where the dependent variable, log (volume) is the logarithmic volume of each trade translated in euro terms, post is an indicator that takes the value of 1 if the trade is executed after the October 7th 2016, sterling flash crash episode and zero otherwise and long or short are indicators that equal to one when a trader retains a long or short open trade at the time of the crash, respectively. The model is expanded to include trader fixed effect allowing for other fixed effects like calendar date, hour of the day or the symbol of the trade to enter into the equation as a robustness test. In addition, all models are double clustered by trader and calendar day.

Results from estimating equation (1) are shown in Table 6 for both long and short traders' categorizations. The Net Long / Net Short in columns 1 to 3 and the Only Long / Only Short in columns 4 to 6. The three different columns for each long/short classification report separately the results when including all the trading activity of retail investors, the trading activity on GBP based instruments and the trading activity on non-GBP based instruments respectively. Further, we present results in three different panels in which the active trader is defined differently. In Panel A we show the two month trading activity of clients who have at least one GBP-trade 28 days before and at least one 28 days after the event; in Panel B we present results for the traders who were active in a narrower time window , specifically those are the traders who places at least one a GBP-trade 14 days before the event and at least one 14 days after the event; in Panel C we illustrate the outcomes when we use traders who were active in an even narrower time window and that is the traders who have at least one GBP-trade 7 days before the event and at least one 7 days after the event.

At a first glance, we observe an overall asymmetric reaction in the trading behavior of long and short traders with the magnitude of the significance changing depending on the time frame that an active investor is defined. Starting from the results considering the closest to the event active traders (Panel C), we observe that using their overall trading activity (columns 1 and 4), traders with short positions at the time of the crash increase their average trading volume after the event (the average trading volume increases by about 10.5%[79] for both Net Short and Only Short traders and is statistically significant at the 5% and the 10% level respectively) while traders with long positions at the time of the crash reduce it (with an average decrease in Net Long (Only Long) investors trading volume to be around 7% (14%) and that is statistically significant at the 10% (1%) level). The effect on the long traders is more prevalent when looking at the Only long traders' classification, with no difference in the level of decrease if the instrument used is GBP based or not. The documented impact on the non-GBP trades disappear when expanding the window used to define an active investor to (-14days, +14days) and (-28days, +28 days) illustrated respectively in Panels B and A. On the other hand, the significant increase in average trading volume after the event for clients with a short position at the crash, is similar across both investors' classifications (Net Short and Only Short). On contrary, for long traders, the influence of non- GBP trades strengthens for greater time frames used in determining active investors (Panels B and A). Overall, we observe that in all panels and in both regression specifications (Net Long/ Net Short or Only Long/Only Short) the traders decrease their trading volume in GBP trades by around 5%.

4.1.2. Alternative definition of active investors

We attempt to test our overall results by including in the analysis traders who are not included in our panel regression sample and therefore examine the effects of the sterling flash crash on individuals trading volume under the use of different active investor

[79] Our dependent variable is log transformed therefore the literal interpretation of the estimated coefficients is evaluated by exponentiating the coefficient and subtract one from this number and multiply by 100, $(e^{\beta} - 1)x100$.

definitions. This requires the assumption of zero trading volume in the after-event period. Thus, to carry out with this perception we use cross- sectional regressions of the form:

$$Change\_Log\_volume_i = b_1 + b_2 \text{ long } + b_3 \text{ short} + Controls + \varepsilon_i \quad (2)$$

In the above regression, we use Change_Log_volume as dependent variable, which is define as the difference between the average log volume invested by trader i after the event with the average log volume invested by the same trader before the event. The Change_Log_volume variable enables us to set the average log volume invested by trader i after the event equal to zero for investors who leave our sample due to a non-GBP-trading activity in the after-event period.

We recognize that the cross sectional analysis does not account for differences on trading behavior over the course of time or controlling for trading patterns within time, even though it can provide a general view of the trend that investors display considering the occurrence of the flash crash.

Table 7 presents results for estimation of model (2) under the use of three distinct groups of active investors. The first cross sectional specification involves (a) clients who have not traded in GBP one month after but traded in another currency pair during that time and additionally traded in GBP after the one-month window and (b) clients who have not traded in GBP one month after but traded in another currency pair and have an open position at the time of the crash. The second specification includes clients who have not traded in GBP one month after but traded in another currency pair (regardless of whether the client traded after the one-month window in GBP or not). And finally the third specification includes (a) clients who have no trading in any currency pair, GBP or not, but has traded in GBP after the one-month window and (b) all the clients who have an open position at the time of the crash.

According to the regression estimates in Table 7, we observe that in all different active investors definition, in the after event period, investors with short positions at the time of the crash increase their overall trading volume while traders with a long open position at the time of the crash decrease it. This further supports the asymmetric reaction, also noted in table 6 with the use of panel regression analysis of trade by trade data with individual and calendar date fixed effects and double cluster at the trade and the calendar date level.

4.1.3. Placebo test

To alleviate the concerns on a finding of a persistent behavior and not a behavior obtained due to the occurence of the sterling flash crash, we replicate the analysis in section 4.1.1 and hence the regression of equation (1) using two different placebo dates. First, we use as an event date the 1st of September 2016, which is one month before our actual event and further we use the 1st of June 2016 which is the month of one of the most important periods in Britain since during that month the United Kingdom European Union membership referendum took place. Reported analysis' outcomes in Table 8 Panels A and B confirm the non-stochasticity of the asymmetric response results of table 6. None of the reported coefficients are found to follow the same pattern as the one observed in table 6 and particularly none is found to be significant in any direction. The only statistically significant coefficient is the one referring to the overall behavior of our traders on their GBP trading activity when we use the 1st of June as a placebo date. This finding indicates that after the first of June the traders decrease their overall GBP-trading volume by about 10%.

4.2. Flash Crash effect on Disposition effect

In the second stage of our analysis we examine possible effects on traders' disposition effect due to the occurrence of an external shock, that is the sterling flash crash episode. Existing literature developed different methods for identifying and measuring the disposition effect. One of the most widely used methods is the application of various measures which are based on the Proportion of Losses Realized (PLG) and the Proportion of Gains Realized (PGR), suggested by Odean (1998). Feng and Seasholes (2005) provide a detailed description on the methods used in the literature along with a discussion on the limitations of the PLG-PGR approach at the individual account level. We therefore follow the Feng and Seasholes (2005) suggestion to test the disposition effect by employing survival analysis[80].

More specifically, we use Cox proportional hazard model with multiple observations per trade to examine whether the sterling flash crash episode influenced investors' tendency

[80] Evaluation of disposition effect using survival analysis were also employed by other authors in the literature for both stock market (Coval and Shumway, 2005; Seru et. al., 2010; Vaarmets et. al., 2018) and FX market (Heimer, 2016).

towards the disposition effect. Following Heimer, 2016 who also examine the disposition effect on FX market individuals, each trade's survival time is partitioned into 10-minute intervals and a sale variable is created for setting up the format of our survival data by defining the closed trades ("dead" trades) in the determined event window. Sale is an indicator variable which equals to the value of 0 within all trades observations and equals to the value of 1 at each last trade's observation at which the trade is closed (If the closing of the trade is not included in our sample, sale variable is zero across all observations of the trade and this is what is called in survival analysis terminology, right censored data). The Cox model can be expressed in the following form:

$$h_i(t) = h_0(t) \exp (b_1 * X_{1,i} + b_2 * X_{2,i} + \ldots + b_n * X_{n,i}) \qquad (3)$$

where h(t) is the probability of closing the position i at time interval t, determined by a set of predictors ($x_1, x_2, \ldots x_n$). $h_0(t)$ is the baseline hazard function and represents the hazard when all predictors are equal to zero. Coefficient, bi, greater than zero or hazard ratio, exp (bi), greater than one, indicates that as the value of the predictor changes from zero to one (all of our predictors are dummy variables) the probability of closing the position decreases.

We are interested to assess changes on traders' disposition effect on the after-event period and in addition to test, if there is any change, whether this is based on investors' position type at the time of the crash. To achieve the examination of our research question, we include in our model the fixed and time varying variables, Long, Short, At Gain, Post and their interactions. Long and Short are the fixed variables and are defined in detail in section 3.2.1. Post is an indicator that takes the value of one if the trade opens after the sterling flash crash episode and zero if it opens before. And finally, At Gain is the variable for identifying the disposition effect and is equal to 1 if the trade at each portion interval is sold for a gain or is trading at a paper gain (that is, if we have a buy (sell) trade and the market price is over (below) the purchase (selling) price). Our models are clustered by trader.

As Table 9 shows, the individuals in our sample exhibit a similar behavior with individuals of earlier studies in terms of disposition effect. By looking the hazard ratios of the At Gain variable in both subsamples, GBP and non GBP trading activity, we see that as the At Gain variable changes from 0 to 1, hence the trade changes from losing to winning, the probability of closing the position increases by 99.3% (99.2%) when we consider the GBP-trading activity of the Net Long/Short (Only Long/Short) sample and by 172.4% (172.8%)[81] when we consider the non GBP trading activity. The insignificant estimates of the interaction terms examining the alterations on disposition effect in the post event period of investors with Short (hazard ratio = 1.147 and z-statistic=1.11) and Long (hazard ratio = 0.887 and z-statistic=-1.44) positions at the time of the crash, show that on average those traders in terms of the disposition effect are not influenced differently from the rest of the traders. Based on the hazard ratio of 1.185 (1.186) of Net Long/Short (Only Long/Short) investors in the GBP trading subsample which is statistically significant at the 1% level, all traders in our sample increase the probability of closing a winning trade rather than a losing one, by 18.5%. The reported increase on the investor disposition effect due to the exogenous shock happening, confirms the theoretical argument of Hirshleifer (2001) of exaggeration on investors behavioural biases during periods of high uncertainty. Kumar (2009a) by measuring the one-month idiosyncratic volatility of stocks and splitting estimates into ten decile portfolios, empirically supports the exhibition of stronger behavioural biases, such us overconfidence and disposition effect, during periods of high uncertainty. Our study extents the existing literature by using an exogenous shock on market volatility and investigates FX retail investors behavioural responses. We provide evidence of exhibition of a stronger disposition effect even after an instantaneous market uncertainty shock.

4.3. Does the increased volatility attract risky investors?

At the day of the event, on Friday 7th 2016, the average (median) daily volatility equals to 0.000452 (0.000261) which corresponds to a 4 standard deviations higher value than the normal[82]. Until the next market opening, that is on Monday 10th 2016, the volatility almost returns to its usual levels with the average (median) amount during that day to be 0.000128 (0.000105).

We complement our analysis by testing whether the increased volatility generated by the exogenous market shock attracts investors with high risk tolerance. To proxy risk tolerance we use the average leverage amount used by each investor before the event happening

[81] Feng and Seasholes (2005) by studying the disposition effect on equity individual investors report a hazard ratio of Trading Gain Indicator, TGI (similar to our At Gain variable) equal to 4.3842 (338.42% increase in the probability of selling the position when the trade changes from losing to winning) and provide a detailed explanation of why this number is completely rational to show up.

[82] The average (median) volatility of minute by minute returns over 5 minutes intervals for the period before the event equals to 0.000107 (0.000088).

and we create an indicator that takes the value of 1 if the estimated amount is at least the 500 level and zero otherwise (around 75% of our sample has an average leverage level of at least 500). To test whether risky investors are attracted by increased volatility, we need to recognize investors who choose to enter into the market when the volatility is high. Therefore, we identify those traders that are considered as active on non GBP currencies in the pre event period but they become GBP active in the first day of the event. We use the first day of the event, since as noted before, the volatility during that day, is 4 standard deviations higher than the normal. We then implement a logit regression analysis using as dependent variable the indicator that takes the value of one if the investor places a trade the first day of the event and zero otherwise. We use as a control group the active investors in non GBP currencies for our whole sample period and in Table 10 Model 1, we observe that there is 4% higher probability for investors with high risk tolerance entering into the GBP market at the event's first day. We further implement a propensity score matching method, according to which each active investor attracted by the event is matched with another active investor that is not attracted by the event. The propensity score matching method is employed based on individuals' demographic characteristics, without the use of replacement and a caliper[83] of 0.1. In Table 10 Model 2 we can see that the 4% observed probability of Model 1 increases to 25%. Therefore, there is a significant positive association of high risk investors with the propensity to enter the market when the volatility is extremely high.

5. Conclusions

The main goal of this paper is to examine whether an unpredictable and extremely short-lived exogenous shock can affect individuals trading behavior. Previous studies have concentrated on the examination of investors behavior after an exogenous dramatic life experience event, like the Great Depression, an outbreak of civil violence or a natural disaster such as earthquake, hurricane or tsunami. We focus on an exogenous dramatic trading experience shock, with minimal to nonexistent fundamental effect to exploit any

[83] Caliper is the maximum allowable distance between propensity scores used for matching.

possible influence on individuals trading activity. The October 7th, 2016 sterling flash crash episode offers an excellent field for investigating our research question.

By examining the trading behavior of active GBP-investors around the event and splitting them into those with no open positions at the time of the crash and those with winning or losing open positions at the time of the crash, we find an asymmetric response in the volume movement of individuals, which differs based on their trading position at the time of the incident. More specifically, we show that traders with short position at the time of the crash (winners) seem to increase their trading volume after the event while traders with long open position at the time of the crash (losers) seem to reduce it. The results are robust across different active investors specifications, with the use of different placebo tests thus mitigating any concerns of spotting a persistent pattern on investors behavior.

We extent our analysis to include the examination of possible effects of the sterling flash crash episode on investors' tendency toward the disposition effect. We find that the average investor in our sample exhibits the disposition effect consistent with previous literature in both equity and FX markets. We do not observe an asymmetric effect on the investor disposition effect when we consider their current trading position at the time of the crash, but we observe an overall increase of the disposition effect in the post event period. Our finding aligns with the suggestion of Hirshleifer (2001) and Kumar (2009a) of stronger investors' behavioural biases during periods of high uncertainty and extent their argument by providing evidence of higher exhibition of disposition effect after an instantaneous market uncertainty shock.

We complement our analysis by showing that there is a significant positive association of high-risk investors and the propensity to enter the market when the volatility is extremely high. We observe that there is 4% higher probability for investors with high risk tolerance to enter into the GBP market when the volatility is high, a probability that rises up to 25% when we define a comparable control group with the implementation of propensity score matching method based on demographic characteristics.

These findings highlight the importance of a deeper understanding of the determinants of their trading behavior. Understanding what drives and what configures individuals trading attitude and self-adapting behavior, is of great importance for supervisory authorities for the optimal formation of investors' regulatory protections.

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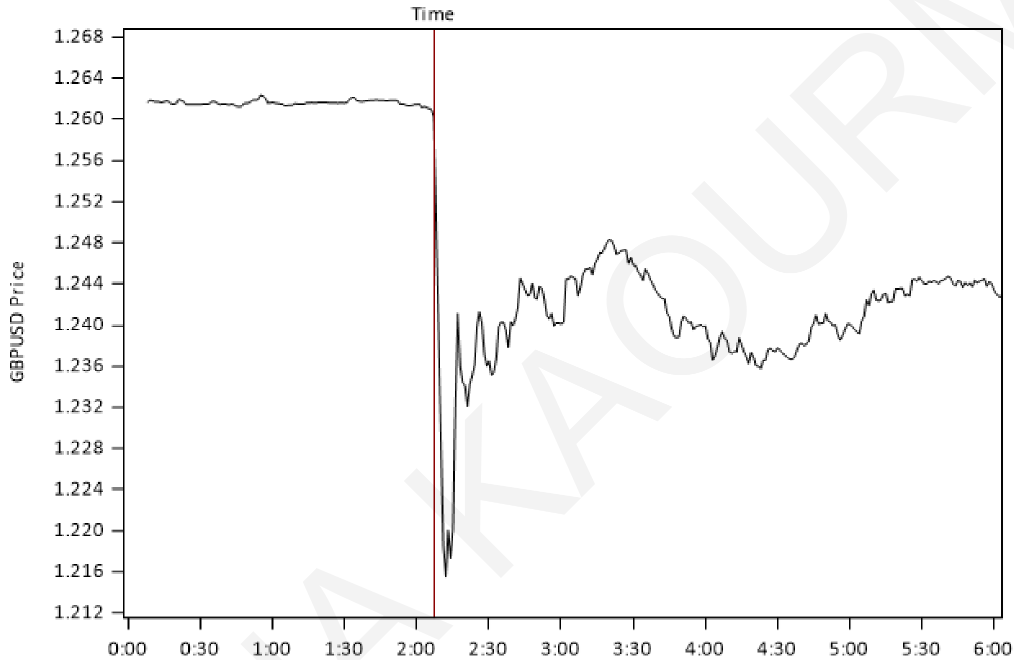
Figure 1: Price and Volatility impact of the sterling flash crash on GBPUSD

Figure 1 Panel A shows the GBPUSD midpoint price movement, [-2hrs, +4hrs] around the October 7, 2016 sterling flash crash, occurred at 02:07:03 (EET). Figure 1 Panel B shows the standard deviation of minute by minute returns, over 5 minutes intervals, for the same time period. Midpoints are defined using the average of bid and ask quotes of the minute by minute spot prices and minute by minute returns are estimated using the log difference of the midpoint at time t with the midpoint at time t-1.

A



B

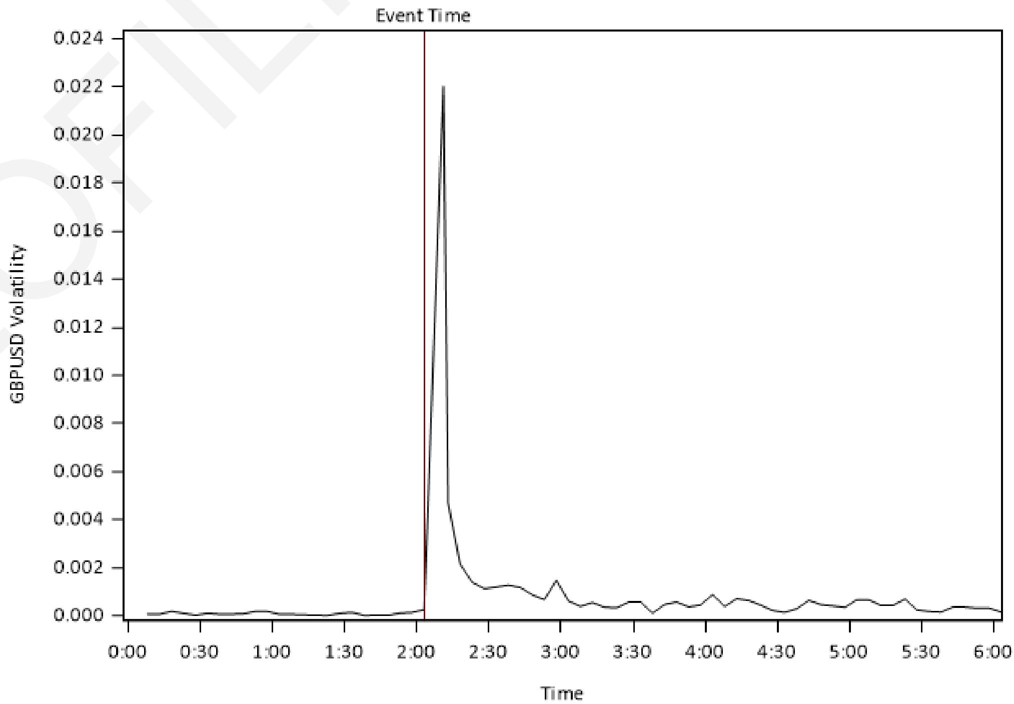
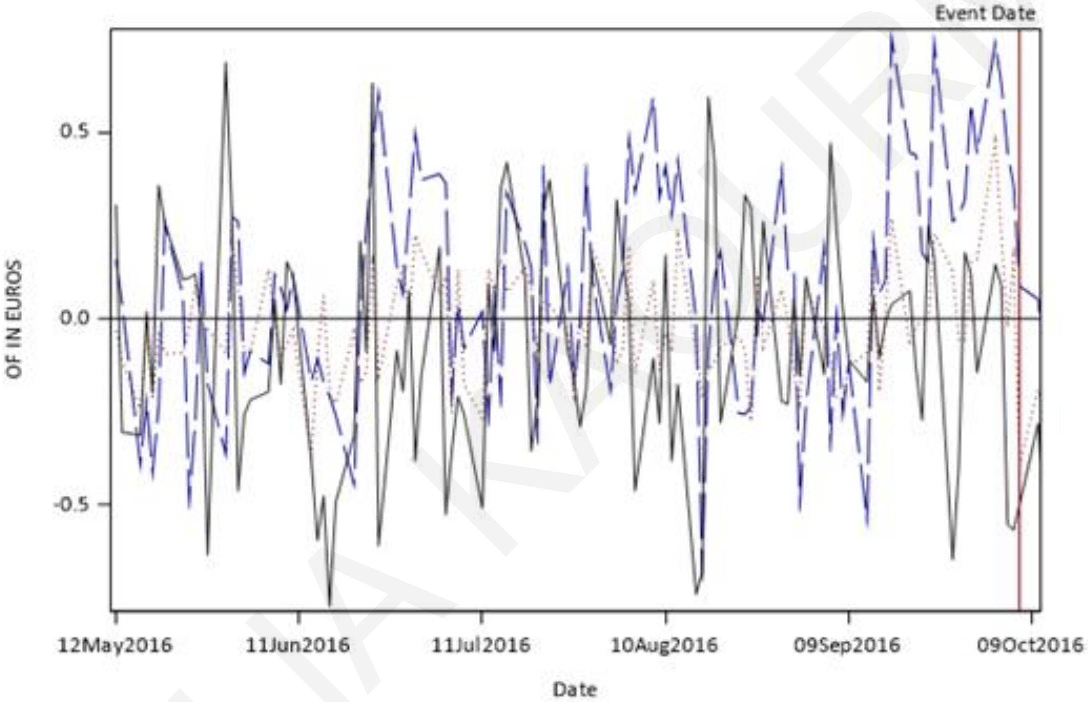


Figure 2: Cumulative average trade imbalance across different traders' groups

Figure 2 shows the cumulative average imbalance for the different traders' categories. Imbalance is estimated as the daily difference between the long and the short volume of each group, divided by the summation of the two. The black solid line, depicts the cumulative average daily imbalance of the traders with net short open positions at the time of the crash, the blue long dashed line the traders with net long open positions and the red short dashed line the rest of the traders in our sample. Figure 2 A use the Net Long/ Short categorization while Figure 2 B use the Only Long / Short categorization.

A



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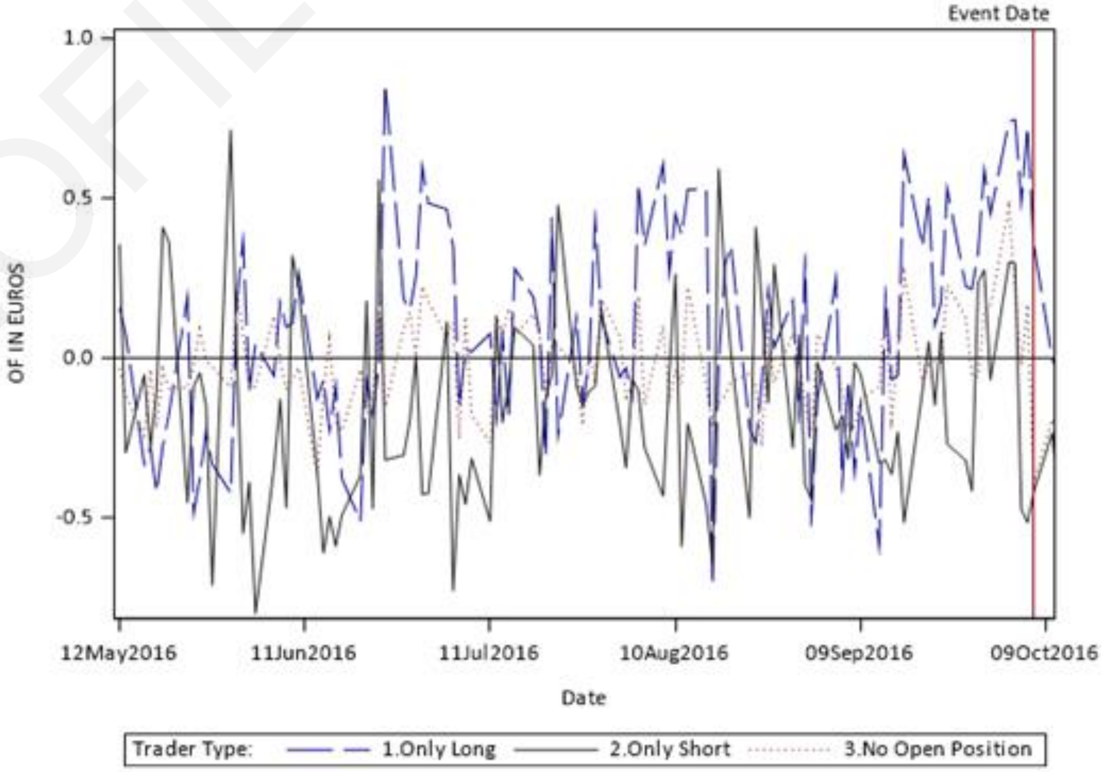

Table 1: Summary Statistics for retail investors' demographic characteristics

This table presents summary statistics for the demographic information considering the 10,563 retail investors who are trading over the period September 9, 2016 to November 4, 2016.

Parameter	Frequency	Percent		Frequency	Percent
Gender					
Mr	7490	84.81	Mrs	1342	15.19
Age					
18-20	119	1.35	50-60	559	6.33
20-30	3020	34.19	60-70	147	1.66
30-40	3336	37.77	70-80	27	0.31
40-50	1623	18.38	80-90	1	0.01
Education Level					
High School	3401	38.51			
BSc	3772	42.71	Doctorate	103	1.17
MSc	978	11.07	None of the above	578	6.54
Employment Status					
Student	735	8.32			
Employed	5222	59.13	Not working	497	5.63
Self-employed	2218	25.11	Retired	160	1.81
Income					
LT 50K	6540	74.05			
50K-100K	1271	14.39	MT 100K	1021	11.56
Net Worth					
LT 50K	5888	66.67			
50K-100K	1285	14.55	500K-1M	326	3.69
100K-500K	582	6.59	MT 1M	751	8.50
Continent					
Africa	614	6.95			
America	457	5.17	Europe	1277	14.46
Asia	6466	73.21	Oceania	18	0.20

Table 2: Summary Statistics for the trading activity at the trade and trader level – All Clients

This table presents descriptive statistics at the trade and trader level. Panel A reports summary statistics for 1,368,793 trades executed by 10,563 clients from September 9 to November4, 2016 and Panel B presents summary statistics for clients' trading activity. Log return is the log difference between the spot open and spot closed price, Log volume is the log volume of each trade in euro terms, Log trade duration reports the log of time in minutes that each trade remains open and dum win is an indicator that takes the value of one when the trade at the closing time is defined as winning and zero otherwise. All those variables are averaged across each client and presented at Panel B. Additionally panel B shows descriptive statistics for num trades event and clients life month variables. Num trades event is defined as the number of trades that each client realized during our sample period and clients life month, indicates clients' trading life in months and is measured as the monthly difference between the date of their last open trade and their first registration date.

Panel A

Variables	N	Mean	Min	P5	P10	P25	P50	P75	P90	P95	Max	Std Dev
log return	1368793	-0.03%	-33.42%	-0.49%	-0.28%	-0.09%	0.02%	0.09%	0.21%	0.34%	13.97%	0.46%
log volume in euro	1368793	7.81	5.26	6.53	6.80	6.91	7.51	8.52	9.36	10.13	15.58	1.17
log trades duration	1368793	4.59	0	1.10	1.79	3.14	4.53	5.99	7.34	8.34	13.87	2.14
dum win	1368793	0.63	0	0	0	0	1	1	1	1	1	0.48

Panel B

Variables	N	Mean	Min	P5	P10	P25	P50	P75	P90	P95	Max	Std Dev
log return	10563	-0.08%	-10.31%	-0.39%	-0.23%	-0.10%	-0.04%	0.00%	0.06%	0.15%	5.29%	0.38%
log volume in euro	10563	7.82	6.46	6.80	6.88	7.03	7.50	8.31	9.27	9.91	13.73	1.03
log trades duration	10563	5.01	0	2.83	3.28	4.00	4.84	5.85	7.01	7.79	13.31	1.55
dum win	10563	0.56	0	0	0.24	0.41	0.58	0.73	0.87	0.96	1	0.25
num trades event	10563	129.58	1	2	4	13	48	135	306	495	13232	306.2
clients life month	10563	23.759	4.0	6.4	8.0	12.6	21.7	34.1	40.8	46.1	84.4	13.0

Table 3: Currency pairs in our sample

This table shows the traded instruments by individual investors during our sample period, which spans from September 9 to November 4, 2016. Currencies are reported by frequency of occurrence in respect to the number of trades, from the most common to the least common. Panel A reports all the currency pairs in our sample and Panel B reports only the currency pairs that include the GBP symbol.

Panel A

All Symbols											
1	EURUSD	11	EURAUD	21	GBPNZD	31	NZDCHF	41	EURPLN	51	NZDSGD
2	GBPUSD	12	AUDJPY	22	GBPCAD	32	USDTRY	42	GBPDKK	52	USDRUB
3	USDJPY	13	GBPAUD	23	CHFJPY	33	EURZAR	43	EURSEK	53	CHFSGD
4	GBPJPY	14	USDCHF	24	EURNZD	34	EURHUF	44	USDHUF	54	GBPSEK
5	AUDUSD	15	AUDCAD	25	GBPCHF	35	EURTRY	45	GBPNOK	55	USDHKD
6	GOLD	26	AUDCHF	26	CADCHF	36	EURNOK	46	USDSEK	56	GBPSGD
7	EURJPY	17	CADJPY	27	EURCHF	37	USDNOK	47	USDDKK	57	EURRUB
8	USDCAD	18	EURCAD	28	NZDCAD	38	EURHKD	48	USDSGD		
9	EURGBP	19	NZDJPY	29	USDMXN	39	EURDKK	49	EURSGD		
10	NZDUSD	20	AUDNZD	30	USDZAR	40	USDPLN	50	SGDJPY		

Panel B

Symbols including GBP											
1	GBPUSD	3	EURGBP	5	GBPNZD	7	GBPCHF	9	GBPNOK	11	GBPSGD
2	GBPJPY	4	GBPAUD	6	GBPCAD	8	GBPDKK	10	GBPSEK		

Table 4: Frequency table for the type of open positions at the crash by number of clients

This table shows the number of clients by the type of open position in GBP at the time of the crash and that is whether the client takes long or short positions with respect to GBP. Panel A splits traders into two categories, Net Long and Net Short which are defined using the difference of the amount of long volume with the amount of short volume. If the difference is positive the client is defined as having Net Long position and if its negative as having Net Short position. Panel B splits traders into three categories: Both measures the number of clients that have long and short positions open at the same, Only Long measures the number of clients that have only long position open and Only Short measures the number of clients that have only short positions open.

Panel A	Active Investors Open At Crash		
Open Type at Crash Net	Frequency	Percent	Cumulative Frequency
Net Long	720	72.58	720
Net Short	272	27.42	992
Panel B	**Active Investors Open At Crash**		
Open Type at Crash	Frequency	Percent	Cumulative Frequency
Both	178	17.94	178
Only Long	596	60.08	774
Only Short	218	21.98	992

Table 5: Logit regressions: Differences between clients with Long versus Short GBP open positions at the crash

The table presents logit regression estimates where the dependent variable is an indicator that takes the value of one if a trader has long open position at the flash crash and zero if he/she has short. Clients are defined as Net Long or Net Short using the difference of the amount of long volume with the amount of short volume. If the difference is positive the client is defined as having Net Long position and if its negative as having Net Short position. Only Long or Only Short are defined as those clients who have only long or only short open positions at the flash crash. Demographic characteristics are incorporated as independent variables. Gender is a dummy variable that takes value equal to one if a trader is a female and zero otherwise and age is the age of the trader in years. A series of dummy variables that take the value of one with respect to each demographic characteristic is also defined. That is, four dummy variables for Education: BSc, MSc, PhD, None; four for Employment: Employed, Self Employed, Not Working, Retired; two for Income: 50 to 100, MT100; four for Net Worth: 50 to 100, 100 to 500, 500 to 1ml and MT1ml and four for trader's continent: Europe, Africa, America and Oceania; High School, Student, and LT50 for Income, Net Worth and Asia are the reference categories for each corresponding variable. For each specification the first column reports the estimates of the logit regression, the second the z - statistics calculated based on robust standard errors and the third column reports variables' marginal effects. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level respectively.

		Net Long / Short			Only Long / Short		
		Coefficient	z-stat	Marginal effect	Coefficient	z-stat	Marginal effect
Variables							
Continent	Europe	-0.07	(-0.34)	-0.014	-0.03	(-0.12)	-0.006
	Africa	-0.24	(-0.88)	-0.046	-0.00	(-0.00)	-0.000
	America	-0.02	(-0.05)	-0.004	0.02	(0.06)	0.004
Education	BSc	-0.14	(-0.84)	-0.028	-0.05	(-0.25)	-0.009
	MSc	0.25	(1.03)	0.049	0.19	(0.67)	0.035
	Phd	0.50	(0.75)	0.097	0.64	(0.79)	0.121
	None of the above	-0.63*	(-1.87)	-0.123*	-0.48	(-1.30)	-0.091
Employment	Student	-0.23	(-0.74)	-0.045	-0.28	(-0.80)	-0.054
	Self Employed	0.01	(0.04)	0.002	0.02	(0.06)	0.005
	Not Working	0.21	(0.43)	0.041	0.38	(0.67)	0.072
	Retired	-0.34	(-0.53)	-0.067	-0.53	(-0.64)	-0.101
Income	50 to 100	-0.13	(-0.53)	-0.025	0.19	(0.67)	0.036
	MT 100	0.46	(1.23)	0.090	0.65	(1.48)	0.122
Net Worth	50 to 100	0.07	(0.29)	0.013	-0.10	(-0.40)	-0.019
	100 to 500	0.30	(0.93)	0.059	0.55	(1.31)	0.105
	500 to 1 ml	-0.81**	(-2.12)	-0.157**	-1.42***	(-3.14)	-0.269***
	MT 1 ml	-0.23	(-0.54)	-0.044	-0.45	(-0.93)	-0.086
Age		0.01	(1.48)	0.003	0.02*	(1.66)	0.003*
Gender		-0.35*	(-1.68)	-0.068*	-0.39	(-1.63)	-0.074
Constant		1.01**	(2.36)		0.90*	(1.88)	
Observations		991		991	813		813
Pseudo R2		0.0210			0.0300		

Table 6: Effects on Investors' Trading Volume due to the Flash Crash

$$\text{Log(volume)}_{jit} = b_1 + b_2 \text{ post} + b_3 \text{ post*long} + b_4 \text{ post*short} + \varepsilon_{jit}$$

The table presents ordinary least square regression results for which the dependent variable, log(volume), is the logarithmic volume of each trade in euro terms. Post is an indicator that takes the value of 1 if the trade is executed after the October 7th 2016, sterling flash crash episode and zero otherwise. Clients are defined as Net Long and Net Short using the difference of the amount of long volume with the amount of short volume. If the difference is positive the client is defined as having Net Long position and if its negative Net Short. Only Long or Only Short are defined as those clients who have only long or only short open positions at the flash crash. The regressions in Panel A (Panel B/ Panel C) use the two-month trading activity of investors who have at least one trade 28 days(14 days / 7 days) window before the event and at least one trade 28 days (14 days / 7 days) after. t -statistics are reported in parentheses and are estimated based on standard errors adjusted for heteroskedasticity and clustered at the trader and date level. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

Panel A: Two-month trading activity around the event. At least one trade before and one after the event in GBP within (-28 days, +28 days).

	Net Long / Short			Only Long / Short		
Variables	All	GBP-Trades	Non GBP-Trades	All	GBP-Trades	Non GBP-Trades
post	-0.00	-0.05*	0.03	0.00	-0.05*	0.03
	(-0.00)	(-1.73)	(1.31)	(0.00)	(-1.73)	(1.32)
post x long	-0.04	-0.05	-0.02	-0.08*	-0.11**	-0.04
	(-1.22)	(-1.21)	(-0.54)	(-1.98)	(-2.59)	(-0.91)
post x short	0.11**	0.07*	0.13**	0.11**	0.07	0.13**
	(2.49)	(1.69)	(2.61)	(2.11)	(1.58)	(2.06)
Observations	879,417	328,045	551,324	805,182	299,989	505,146
adj R^2	0.564	0.582	0.577	0.560	0.580	0.571
Trader	YES	YES	YES	YES	YES	YES
Hour of the Day	YES	YES	YES	YES	YES	YES

Panel B: Two-month trading activity around the event. At least one trade before and one after the event in GBP within (-14 days ,+14 days).

	Net Long / Short			Only Long / Short		
VARIABLES	All	GBP-Trades	Non GBP-Trades	All	GBP-Trades	Non GBP-Trades
post	-0.00	-0.06**	0.03	-0.00	-0.06**	0.03
	(-0.13)	(-2.27)	(1.19)	(-0.12)	(-2.27)	(1.19)
post x long	-0.04	-0.03	-0.03	-0.08*	-0.10**	-0.05
	(-1.10)	(-0.84)	(-0.66)	(-1.95)	(-2.25)	(-1.12)
post x short	0.11**	0.09**	0.13**	0.12**	0.09*	0.13*
	(2.51)	(2.09)	(2.52)	(2.16)	(1.95)	(2.01)
Observations	771,008	296,792	474,183	697,916	269,389	428,494
adj R^2	0.563	0.583	0.575	0.559	0.580	0.569
Trader	YES	YES	YES	YES	YES	YES
Hour of the Day	YES	YES	YES	YES	YES	YES

Table 6 (continued): Effects on Investors' Trading Volume due to the Flash Crash

Panel C: Two-month trading activity around the event. At least one trade before and one after the event in GBP within (-7 days ,+7 days).						
	Net Long / Short			Only Long / Short		
VARIABLES	All	GBP-Trades	Non GBP-Trades	All	GBP-Trades	Non GBP-Trades
post	0.02	-0.05*	0.05*	0.02	-0.05*	0.05*
	(0.54)	(-1.81)	(1.70)	(0.54)	(-1.80)	(1.70)
post x long	-0.07*	-0.05	-0.07	-0.13***	-0.11**	-0.11**
	(-1.83)	(-1.02)	(-1.49)	(-2.84)	(-2.42)	(-2.11)
post x short	0.10*	0.08*	0.11*	0.10*	0.09*	0.11
	(2.01)	(1.89)	(2.01)	(1.76)	(1.78)	(1.61)
Observations	647,080	256,430	390,623	576,194	229,751	346,416
adj R^2	0.565	0.586	0.579	0.561	0.584	0.572
Trader	YES	YES	YES	YES	YES	YES
Hour of the Day	YES	YES	YES	YES	YES	YES

Table 7: Different definitions of active investors to test the effects on Investors' Trading Volume due to the Flash Crash

$$Change\_Log\_volume_i = b_1 + b_2 \text{ long} + b_3 \text{ short} + \text{controls} + \varepsilon_i$$

The table presents cross sectional regression results for which the dependent variable is the Change_Log_volume which is defined as the difference between the average log volume invested by trader i after the event with the average log volume invested by the same trader before the event. Volume is in euro terms. There are four different definitions of active investors in which we set the volume after the event to be equal to zero for clients that have not traded in GBP during that time but satisfy other criteria to allow them to be considered as active. Clients are defined as Net Long or Net Short using the difference of the amount of long volume with the amount of short volume. If the difference is positive the client is defined as having Net Long position and if its positive Net Short. Only Long or Only Short are defined as those clients who have only long or only short open positions at the flash crash. In all regression specifications demographic characteristics are incorporated as control variables. t -statistics are reported in parentheses and are estimated based on robust standard errors. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

		Net Long / Short			Only Long / Short		
Definition of active investor	Variables	# Investors	Coefficient	tstat	# Investors	Coefficient	tstat
Panel Regression Specification: At least one trade before and one trade after the event in GBP.	long short	4,021	-0.04 0.08**	(-1.26) (2.37)	3,843	-0.05 0.07**	(-1.63) (1.97)
Set volume after the event=0 if (a) the client has not traded in GBP one month after but traded in another currency pair during that time and traded in GBP after the one-month window. (b) client has not traded in GBP one month after but traded in another currency pair and has an open position at the time of the crash.	long short	4,688	-0.05* 0.08**	(-1.73) (2.34)	4,502	-0.06** 0.07**	(-2.16) (2.00)
Set volume after the event=0 if the client has not traded in GBP one month after but traded in another currency pair (ignoring whether the client traded after the one-month window in GBP or not).	long short	4,927	-0.04 0.08**	(-1.52) (2.54)	4,741	-0.06** 0.08**	(-1.97) (2.17)
Set volume after the event=0 if (a) the client has no trading in any currency pair, GBP or not, but has traded in GBP after the one-month window. (b) client has an open position at the time of the crash.	long short	5,555	-0.43*** 1.07***	(-3.96) (11.85)	5,354	-0.58*** 1.09***	(-4.86) (11.34)

Table 8: Effects on Investors' Trading Volume using a placebo event

$$Log(volume)_{jit} = b_1 + b_2\ post + b_3\ post*long + b_4\ post*short + \varepsilon_{jit}$$

The table presents ordinary least square regression results for which the dependent variable, log(volume), is the logarithmic volume of each trade in euro terms. Post is an indicator that takes the value of 1 if the trade is executed after the placebo date and zero otherwise. Clients are defined as Net Long and Net Short using the difference of the amount of long volume with the amount of short volume. If the difference is positive the client is defined as having Net Long position and if its negative Net Short. Only Long or Only Short are defined as those clients who have only long or only short open positions at placebo date. t -statistics are reported in parentheses and are estimated based on standard errors adjusted for heteroskedasticity and clustered at the trader and date level. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

Panel A: The effect of a placebo event set at September 1st, 2016 on investors trading volume

	Net Long / Short			Only Long / Short		
VARIABLES	All	GBP-Trades	Non GBP-Trades	All	GBP-Trades	Non GBP-Trades
post	-0.01	0.01	-0.03	-0.01	0.01	-0.03
	(-0.59)	(0.25)	(-0.96)	(-0.59)	(0.25)	(-0.96)
post x long	0.04	0.04	0.03	0.03	0.06	0.02
	(0.93)	(1.20)	(0.71)	(0.71)	(1.58)	(0.32)
post x short	0.01	-0.01	-0.00	0.01	-0.01	-0.00
	(0.10)	(-0.14)	(-0.02)	(0.13)	(-0.10)	(-0.01)
Observations	766,448	280,972	485,320	711,005	259,097	451,757
adj R^2	0.581	0.595	0.593	0.580	0.594	0.592
Trader	YES	YES	YES	YES	YES	YES
Hour of the Day	YES	YES	YES	YES	YES	YES

Panel B: The effect of a placebo event set at June 1st, 2016 on investors trading volume

	Net Long / Short			Only Long / Short		
VARIABLES	All	GBP-Trades	Non GBP-Trades	All	GBP-Trades	Non GBP-Trades
post	-0.05*	-0.10***	-0.03	-0.05*	-0.10***	-0.03
	(-1.92)	(-3.10)	(-1.29)	(-1.92)	(-3.09)	(-1.30)
post x long	0.03	0.04	0.02	-0.01	0.03	-0.02
	(0.60)	(0.80)	(0.36)	(-0.15)	(0.56)	(-0.34)
post x short	0.02	0.04	-0.02	0.07	0.10	-0.00
	(0.33)	(0.68)	(-0.35)	(0.84)	(1.23)	(-0.04)
Observations	795,568	281,862	513,568	740,665	258,044	482,493
adj R^2	0.532	0.553	0.544	0.530	0.554	0.540
Trader	YES	YES	YES	YES	YES	YES
Hour of the Day	YES	YES	YES	YES	YES	YES

Table 9: Disposition effect pre and post the sterling flash crash episode

This table presents hazard ratios associated with how loss or gain influenced the decision of individuals to hold or close their trade position. Each trade is expanded from its open time to its closed time setting our model to have multiple observations per trade and estimating the failure rate with the use of a dummy variable that takes a value of zero at every 10-minute interval that individuals hold a currency instrument, and the value of one if they decide to sell it. As risk factors we set four different variables along with their interactions. At Gain, is an indicator that takes a value of one every 10-minute interval that the instrument is trading at a gain (relative to the purchase price) and zero otherwise, Post is an indicator that takes the value of 1 if the trade is executed after the October 7th 2016, sterling flash crash episode and zero otherwise and long/short are also dummy variables that equal to one when a client has a long/short open position at the time of the crash. Net Long and Net Short are estimated using the difference of the amount of long volume with the amount of short volume. If the difference is positive the client is defined as having Net Long position and if its negative Net Short. Only Long or Only Short are defined as those clients who have only long or only short open positions at the flash crash. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level, respectively.

	GBP-Trades		Non GBP-Trades	
Variables	Net Long / Short	Only Long / Short	Net Long / Short	Only Long / Short
At_Gain	1.993***	1.992***	2.724***	2.728***
	(18.79)	(18.79)	(23.84)	(23.80)
Post	1.013	1.012	0.999	0.998
	(0.36)	(0.35)	(-0.06)	(-0.08)
At_Gain x Post	1.185***	1.186***	0.959	0.959
	(3.49)	(3.50)	(-1.25)	(-1.25)
Long	0.453***	0.515***	0.455***	0.540***
	(-12.61)	(-11.61)	(-13.08)	(-9.34)
At_Gain x Long	2.063***	1.803***	1.892***	1.603***
	(8.41)	(6.97)	(8.23)	(5.51)
Post x Long	1.027	1.072	1.117**	1.107*
	(0.42)	(0.97)	(2.17)	(1.75)
At_Gain x Post x Long	0.887	0.862	0.965	0.896
	(-1.44)	(-1.57)	(-0.56)	(-1.50)
Short	0.741***	0.891	0.682***	0.851*
	(-2.71)	(-0.98)	(-4.03)	(-1.70)
At_Gain x Short	1.147	0.950	1.085	0.920
	(1.11)	(-0.38)	(0.72)	(-0.63)
Post x Short	0.956	0.972	1.052	1.008
	(-0.44)	(-0.25)	(0.80)	(0.10)
At_Gain x Post x Short	0.889	0.932	0.918	1.039
	(-0.95)	(-0.47)	(-0.95)	(0.36)
Observations	9,283,063	7,871,577	22,103,012	18,780,529

Table 10: Does the increased volatility attract risky investors

The table presents logit regression estimates where the dependent variable, is an indicator that takes the value of one if the investor places a trade the first day of the event and zero otherwise. To proxy high risk investors we use the average leverage amount of all trades executed by each investor before the event happening and we create the dummy which takes the value of 1 if the estimated amount is at least the 500 level and zero otherwise. All demographic characteristics are incorporated as control variables. For each specification the first column reports the estimates of the logit regression, the second the z -statistics calculated based on robust standard errors and the third column reports variables' marginal effects. ***, ** and * denote statistical significance (SS) at the 1%, 5% and 10% level respectively.

	Model 1			Model 2		
VARIABLES	Coefficient	z-stat	Marginal effect	Coefficient	z-stat	Marginal effect
high_leverage	0.88**	(2.34)	0.042**	1.07*	(1.70)	0.253*
Constant	-3.08***	(-3.96)		-1.97*	(-1.72)	
Observations	1,325		1,325	134		134
Pseudo R2	0.0709			0.0369		

General Conclusion

There is a substantial literature investigating the trading behavior of individual investors in stock market but limited work has been done in FX market. With the utilization of a proprietary intraday dataset on individuals trading activity in FX market, this thesis aims to investigate several aspects of retail investor trading behavior and extends our knowledge about their trading attitude.

The first chapter investigates the effects of news sentiment and scheduled macro news announcements on retail investors order flow. Taking advantage of a proprietary dataset that includes the aggregate of long and short positions of retail investors in EURUSD exchange market, the individuals net order flow is constructed and analysis results suggest a significant contrarian reaction around scheduled macro news announcements which is mostly driven by individuals return-contrarian behavior rather than the surprise of the announcement itself. Further, a time series analysis reveals individuals' return-contrarian behavior on an intraday basis as well as the predicting power of the rolling 30-minute lagged sentiment change on their trading activity. Statistically significant returns with the employment of a simple cross over trading strategy that generates signals opposite to what indicated by individual investors net order flow, showing that collectively individuals investors order flow has no information about future FX returns but helps in the stabilization of the market through their liquidity provision role.

The second chapter uses the disaggregated trade by trade data along with the investor characteristics and provides an examination of the heterogeneous risk-taking behavior among individual investors. A key innovation of this project is the use of leverage level, a widely used mechanism in the forex market, to obtain a direct dimension to explore investors' attitude toward risk. As existing literature proposed young, educated investors, with higher employment status and very high income and net worth are willing to accept higher levels of risk. Moreover, Asian traders are generally engaged in greater risk levels, followed by Africans, Europeans, Americans and finally traders from Oceania. The fact that women appear to engage in higher risk levels that men, is an unanticipated outcome, implying that women in FX market are significantly different from women in equity market. Motivated by this unexpected finding and splitting by gender to examine how individuals adjust their risk taking behavior after losses or gains, evidence suggests that male investors are prone to self-attribution bias, while women are not. Matching women with men by demographic characteristics and comparing similar samples, the behavioural gender difference disappears, demonstrating that other demographic variations determine the exhibition of the bias, rather than gender. In particular, characteristics that represent sophisticated investors decrease the probability of exhibition of self-attribution bias.

The last chapter uses the sterling flash crash episode and exploits possible effects on retail investors trading behavior. The current study contributes to the literature that examines the exogenous determinants of personal experience. Unlike related research that uses exogenous dramatic life experience events, this study utilizes the sterling flash crash incident which can be determined as an exogenous dramatic trading experience shock. Empirical results are supporting the asymmetric response on individuals trading volume which differs based on their trading position at the time of the incident. Further analysis on traders disposition effect find no asymmetric impact on individuals regarding their trading position, nevertheless there is an overall increase on the levels of the bias, suggesting that an instantaneous market shock can exaggerate the exhibition of the disposition effect of individual investors.

Our findings support the continuous vigilance of forex monitoring authorities and provide further guidance for helping individual investors to make better investment decisions.