Investor Sentiment and (Anti) Herding in the Currency Market: Evidence from Twitter Feed Data*

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Abstract

This paper establishes a direct link between (anti) herding behavior in currency markets and investor sentiment, proxied by a social media based investor happiness index built on Twitter feed data. Our analysis of daily data for nine developed market currencies suggests that the foreign exchange market is generally characterized by strong anti-herding behavior. Utilizing the quantile-on-quantile (QQ) approach, developed by Sim and Zhou (2015), we show that the relationship between investor sentiment and anti-herding is in fact regime specific, with anti-herding behavior particularly prominent during states of extreme investor sentiment. The effect of sentiment on anti-herding is generally stronger in extreme bullish sentiment states, while average sentiment is associated with less severe anti-herding. The findings lend support to the behavioral factors for asset pricing models and suggest that real time investor sentiment signals can be utilized to monitor potential speculative activities in the currency market.

Keywords: Herding, Exchange Rates, Time-varying Regression, Investor Happiness.
JEL Codes: G15, G40

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1 Introduction

Classic economic theory which builds on the concept of an efficient market setting (Fama (1965, 1970)) argues that investor decisions are based on rational expectations that utilize all available information in an efficient manner. Challenging the efficient market hypothesis (EMH), however, Scharfstein and Stein (1990) argue that professional managers often tend to 'follow the herd' for a variety of behavioral factors that might impact decision making at the individual level. Devenow and Welch (1996) define herding in terms of correlated trading patterns across individual investors such that investment decisions across similar asset classes display correlated patterns as a result of inefficient processing of either common or private information. Clearly, such informational inefficiencies can lead to systematic, sub-optimal decision making by an entire population of investors, resulting in (among others) market bubbles and frenzies. Indeed, as Bikhchandani and Sharma (2000) note, herding increases the fragility of the financial system and contributes to return volatility in financial markets.

The literature distinguishes between rational and irrational herding to explain herding mechanisms emanating from various price signals. Rational herding focuses on payoff externalities, that is, the payoff from an action increases the chances that others will follow the same action (see Hirshleifer et al. (1994) and Dow and Gorton (1994)). Alternatively, the principal-agent perspective argues that managers will engage in market-mimicking strategies in order to preserve their reputation or maintain stability in their compensation as compensation schemes are often tied to aggregate market benchmarks (see Rajan (1994)). In yet another theory, informational cascades are argued to form as investors substitute private information with inferences obtained from the actions of other "more informed" investors (see Welch (1992)), often due to the costs associated with information acquisition at the individual investor level (Calvo and Mendoza (2000)). Although the aforementioned theories approach herding behavior as a rational form of decision making, the proponents of irrational herding view rational decision making among investors as a fallacy and underline the presence of psychological, environmental, and social factors that contribute to herding behavior among investors (see Shiller (2000, 2003)).

A popular approach to detect herding in empirical studies utilizes the cross-sectional dispersion in asset returns, which aims to capture the similarity in return behavior around the market consensus (Christie and Huang (1995)). According to Christie and Huang (1995), the dispersion of asset returns would be significantly lower in the presence of herding (i.e. asset returns display greater directional similarity as investors exhibit correlated trading behavior moving funds in and out of certain asset classes simultaneously), while individual asset returns will deviate significantly from the market consensus during periods of anti-herding. Building on this argument and thanks to the evolution of behavioral asset pricing models in the recent literature, not surprisingly, herding has been intensely examined by focusing on return dispersion patterns in the stock market (Christie and Huang (1995), Chang et al. (2000), BenSada (2017), Economou et al. (2016), Mobarek et al. (2014), Kremer and Nautz (2013), Gebka and Wohar (2013), Balcilar et al. (2013), Babalos and Stavroyiannis (2015a), Klein (2013), Economou et al.

(2011), Venezia et al. (2011), Lao and Singh (2011), Chiang and Zheng (2010), Demirer et al. (2010), Chiang and Zheng (2010), Tan et al. (2008), and Demirer and Kutan (2006)), futures market (Gleason et al. (2003)), Real Estate Investment Trusts (REITs) (Philippas et al. (2013)), exchange traded funds (ETFs) (Gleason et al. (2004)), and various commodities (Adrangi and Chatrath (2008), Balcilar et al. (2014), Babalos and Stavroyiannis (2015a), Babalos et al. (2015))). With the advance of improved econometric techniques, the literature has shifted the focus to the dynamic nature of herding in order to understand how herd behavior evolves in times of crisis or panic (Babalos et al. (2015), Balcilar et al. (2013), Babalos and Stavroyiannis (2015a), and Klein (2013)). Motivated by the growing evidence that links investor sentiment to financial market anomalies (e.g. Baker and Wurgler (2006); Frazzini and Lamont (2008) and Antoniou et al. (2013); Huang et al. (2015)) and the evidence that links investor sentiment to herding and speculative behaviour in financial markets (e.g. Lemmon and Ni (2011); Blasco et al. (2012)), this study provides a novel perspective to the dynamic nature of herding behavior in the currency market by examining the dynamic role of sentiment on herding and anti-herding behavior among currency market participants.

Examining herding behavior in the currency market is motivated by the fact that the foreign exchange market is the largest and most liquid financial market globally, with multiple times the daily volume of international trade flows and stock market transactions executed daily. Given that the same currency can be traded at multiple markets at the same time, the currency market enjoys ample liquidity and market-making activity by a wide variety of investors including hedgers, speculators and arbitrageurs. The importance of studying herding in foreign exchange markets is illuminated by Belke and Setzer (2004) who argue that currency market volatility is generally caused by factors other than changes in fundamental macroeconomic conditions (such as behavioral factors), particularly in emerging markets. This is indeed supported by the evidence of price cascades in currency markets due to stop-loss orders (Osler, 2005), which can be driven by the informational cascades proposed in the earlier literature (e.g. Welch (1992)). The possible presence of herding behavior in the currency market is further motivated by the evidence of commonalities in currency traders' risk preferences (e.g. Dominguez and Frankel (1993); Carlson (1998); Bensaid and De Bandt (2000); Mende et al. (2004); Osler (2005); Bjønnes and Rime (2005)) and the recent evidence that links the time-variation in risk preferences to currency excess returns (Demirer and Yuksel (2021)) and the profitability of carry trades (Demirer et al. (2020)). Interestingly, however, although several studies were conducted to examine herding in the foreign exchange market, they remain limited in volume and the utilisation of the empirical measures to detect herding (see Kim et al. (2004), Park (2011), Pierdzioch et al. (2012) and others).

This paper adds to the literature on herding in financial markets by establishing a direct link between (anti) herding behavior in currency markets and investor sentiment, proxied by a social media based investor happiness index built on Twitter feed data. Unlike other studies that are limited by linear (or static) models to detect herding, we utilize the quantile-on-quantile (QQ) approach, developed by Sim and Zhou (2015), in order to capture the regime specific patterns that drive the linkage between cross-sectional dispersion of currency returns and sentiment regimes. Our analysis of daily data for nine developed market currencies suggests that the foreign exchange market is generally characterized by strong anti-herding behavior. The analysis of quantile-on-quantile relationships further suggests that the relationship between investor sentiment and anti-herding is in fact regime specific, with anti-herding behavior particularly strong during states of extreme investor sentiment. The effect of sentiment on anti-herding is generally stronger in extreme bullish sentiment states, while average sentiment is associated with less severe anti herding. The findings lend support to the behavioral factors for asset pricing models and suggest that real time investor sentiment signals can be utilized to monitor potential speculative activities in the currency market. The remainder of the paper is structured as follows. In Section 2, we present a brief review of the literature on herding in financial markets and the role of sentiment on market anomalies. Section 3 presents the data and methodology outlining the herding model, the econometric methods employed to examine the role of investor sentiment on herding. This is followed by a discussion of the results in Section 4 and finally, Section 5 concludes.

2 Literature Review

A growing number of studies in the literature present robust evidence that links investor sentiment to anomalies and excess returns in financial markets (e.g.Baker and Wurgler (2006); Frazzini and Lamont (2008) and Antoniou et al. (2013); Huang et al. (2015)). Motivated by the evidence that links investor sentiment to herding and speculative behaviour in financial markets (e.g. Lemmon and Ni (2011); Blasco et al. (2012)), Demirer et al. (2020) and Demirer and Yuksel (2021) further extend the literature to the currency market and establish a link between the time variation in risk preferences, as a proxy for sentiment, to excess currency returns and the profitability of carry trades. When it comes to herding or anti-herding behavior in the currency market, however, the role of investor sentiment is relatively understudied. The literature that examines herding in the currency market provides mixed results at best. For example, Kim et al. (2004) find evidence of herding in the won-dollar exchange rate market using the power-law approach, while Park (2011) documents evidence of asymmetric herding in the USD/JPY and USD/KRW markets using the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) techniques. At the same time, Pierdzioch et al. (2012) document evidence of anti-herding behaviour amongst exchange rate forecasters in emerging markets, while Russell (2012) explores how herding informs changes in the exchange rate regime choice by the government. In more recent studies, focusing on the time-varying nature of herding, Tsuchiya (2015) shows evidence of herding (anti-herding) over time (including times of crisis) amongst exchange rate forecasters.

Although the drivers of herding in foreign exchange markets remain a subject of debate, a separate strand of the literature has established a link between herding and investor sentiment in equity markets (Da et al. (2015), Garcia (2013), Liao et al. (2011), Bathia and Bredin (2013), Gavriilidis et al. (2016), and Blasco et al. (2018)). While Vieira and Pereira (2015) find weak evidence of a relationship between herding and investor sentiment in small European markets, Gavriilidis et al. (2016) show that herding was stronger during the Ramadan period where investor optimism is enhanced. Similarly, focusing on the U.K., Blasco et al. (2018) show that herding tends to be stronger in periods of market stress when analysts are forced to release negative information in periods of pronounced investor sentiment. Although these studies have largely focused on herding in equity markets, the evidence on the currency market suggests the possible presence of herding or anti-herding behavior among currency traders via feedback trading and price cascades induced by stop-loss orders. Feedback trading implies that investors rely on past price information to formulate current trade positions and has been studied extensively in the context of currency market (for example Tayeh and Kallinterakis (2020), Laopodis (2005), and Aguirre and Saidi (1999)). In this context, Ferreira and Kallinterakis (2006) note that a feedback investor follows the direction of historical price patterns, while an investor who herds follows the actions of others. Thus, it is possible that herding can precede the decision to positive or negative feedback trade. A similar set of circumstances is feasible for price cascades (Osler (2005)) in the event of, for example, an exogenous loss limit in currency markets. Furthermore, several other studies(e.g. Carlson (1998) and Dominguez and Frankel (1990)) have suggested risk aversion commonalities amongst currency market participants as a result of prudential regulations. Therefore, it can be argued that collective behavioural patterns by investors (herding) in currency markets can potentially lead to feedback trading, mispricing and excess volatility (Ferreira and Kallinterakis (2006)). To that end, investor happiness utilized in our empirical application provides a valuable opening to capture the dynamic changes in sentiment as it is extracted from real time Twitter feed data.

Indeed, utilizing investor happiness as a proxy for investor sentiment, Bonato et al. (2020) outline the importance of investor happiness in explaining the first and second moments in stock market returns, thus establishing the baseline evidence that links investor happiness to return and volatility dynamics in financial markets. In the literature, investor happiness is measured mainly in two ways. The first involves the use of market indicators such as initial public offerings (IPOs) and volatility measures such as the implied volatility index (VIX) (for example, Bathia and Bredin (2013)). A drawback of this approach is that these market indicators often reflect information related to other economic fundamentals than just investor sentiment (Da et al. (2015)). The second is a survey-based approach based on indices such as the UBS/GALLUP index for investor optimism (for example, Brown and Cliff (2004)). Other measures that rely on daily internet search data have been used as well. However, Da et al. (2015) underscores the move in the literature toward non-market high-frequency measures as the market-based measures that are available at a high frequency can reflect more than just investor sentiment. As a result of the move towards survey-based sentiment indices, numerous studies have examined herding in relation to sentiment proxies (e.g. Garcia (2013), Liao et al. (2011), Bathia and Bredin (2013), Gavriilidis et al. (2016), and Blasco et al. (2018)). Although not directly linked to herding, examining investor sentiment during recessions via a measure of the fraction of positive to negative words in two financial market outlets, Garcia (2013) shows a link between investor sentiment and the average return on the Dow Jones Index. Similarly, using principal component analysis, Liao et al. (2011)

find that investor sentiment plays a significant role in explaining fund manager herding via informational cascades suggested in the earlier literature. Likewise, Bathia and Bredin (2013) find no evidence of sentiment spillovers from the U.S. to the G7 markets although this study uses the survey-based Baker and Wurgler (2006) composite sentiment index. In all, despite the ample evidence of a link between sentiment and equity market herding, the literature is relatively light for currencies although separate strands of the literature present argument towards the presence of herd or anti-herd formation by currency traders.

3 Data and Methodology

3.1 Data

We focus on nine developed market currencies as shown in Figure A.1 in Appendix A, with the USD as the common denominator. More specifically, we examine the Australian dollar (AUD), Canadian dollar (CAD), euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK), Swiss franc (CHF), and British pound (GBP). The daily exchange rate data is sourced from the Global Financial Database.[1] After accounting for missing data, our sample covers from 2003-07 to 2019-07. As will be discussed later, following Xie et al. (2015), we construct a measure of dispersion across currency returns by using the trade-weight of each country with the U.S. For this purpose, we obtain trade weight data from the Bank of International Settlements (BIS).[2] The BIS data are available in three-year intervals from 1990 to 2016. These are converted to a daily frequency assuming that the trade weights do not display significant deviations at the daily level with respect to the three-year weights that are available.[3] Daily currency returns, R_t, are calculated as

$$R_t = \left(\frac{E_t}{E_{t-1}} - 1 \right) \times 100 \, , \tag{1}$$

where E_t and E_{t-1} is the exchange rate at time t and $t-1$. The return series are plotted in Figure A.2 in Appendix A.

As stated earlier, the literature offers alternative methods to capture investor sentiment and the survey-based approach has recently gained more credibility as the use of market indicators such as initial public offerings (IPOs) and volatility measures such as the implied volatility index (VIX) (e.g. Bathia and Bredin (2013)) provide a biased measure of sentiment, capturing information regarding economic phenomena rather than just sentiment. Given this argument and in line with Da et al. (2015), we use the investor happiness index, Hedonometer, as a non-market based sentiment proxy, which measures investor happiness based on Twitter user-generated data. The happiness index is constructed from the online expressions extracted from social media feeds (Twitter), based

[1] https://www.globalfinancialdata.com
[2] https://www.bis.org/statistics/eer.htm
[3] The daily trade weights are shown in Figure B.1 in Appendix B.

on how people present themselves to the world on Twitter. To obtain this index, 10,000 unique words are scored on a nine-point scale which varies from 1 (sad) to 9 (happy), while uncommon words are included occasionally and the index is updated daily.[4] This index has been utilized in several studies as a non-market based sentiment proxy available at high frequency (Sibley et al. (2016), Reboredo and Ugolini (2018), and You et al. (2017)). In our context, considering the evidence that links investor sentiment to herding and speculative behaviour in financial markets (e.g. Lemmon and Ni (2011); Blasco et al. (2012)) and the link between currency excess returns and time-varying risk preferences (e.g. Demirer et al. (2020); Demirer and Yuksel (2021)), we explore the role of sentiment as a determinant of herding or anti-herding behavior in the currency market. The investor happiness index is plotted in Figure A.3.

3.2 Static Model of Herding

Following Christie and Huang (1995) and Chang et al. (2000) we calculate two dispersion metrics. That is the cross-sectional standards deviation (CSSD) and the cross-sectional absolute standard deviations (CSAD). However, instead of assuming equal weighting of the markets, we use the respective trade weight of each market with the US (see Xie et al. (2015)). These are calculated for all markets as follows:

$$CSSD_t = \sqrt{\sum_{i=1}^{N} w_{i,t}(R_{i,t} - R_{m,t})^2}\,, \tag{2}$$

$$CSAD_t = \sum_{i=1}^{N} w_{i,t}|R_{i,t} - R_{m,t}|\,, \tag{3}$$

where $R_{i,t}$ observed currency returns from market i at time t, $R_{m,t}$ is a trade-weighted average of the $R_{i,t}$, $w_{i,t}$ is the respective trade weight of each market over time with the US, and the $\sum_i w_{i,t} = 1$. The return dispersion measures in Equations 2 and 3 capture the directional similarity across currency returns at a given point in time with respect to the aggregate market. Herding tests, in turn, are based on the pattern of return dispersions during periods of large price movements. Note that standard pricing models predict return dispersion to be positively associated with market returns, which is implied by the positive value of the first derivative of the CSAD term with respect to market return. However, Chang et al. (2000) argue that, during periods of large price fluctuations, i.e. when herding is more likely to occur, the positive relation between the market return and return dispersion will break down and herding will be evidenced by lower return dispersions during such periods. Having computed the cross-sectional return dispersion in currency returns, we follow Chang et al. (2000) and examine the pattern of return dispersions during periods of large price movements. The rationale behind the testing methodology is that, if herding is present, the correlated trades by

[4] The happiness index is available at https://hedonometer.org/timeseries/en_all/

investors would lead to a greater directional similarity in currency returns, thus leading to lower dispersion in returns. As such behavior would be more likely during periods of market stress, characterized by large price fluctuations, we examine the relationship between return dispersion and $R_{m,t}$ and $R^2_{m,t}$ and focus on how return dispersions relate to the quadratic term in the model. To that end, we estimate

$$CSSD_t = a_0 + a_1|R_{m,t}| + a_2 R^2_{m,t} + \epsilon_t \,, \tag{4}$$

$$CSAD_t = a_0 + a_1|R_{m,t}| + a_2 R^2_{m,t} + \epsilon_t \,. \tag{5}$$

where a_2 is the herding coefficient. Following a single factor pricing model, we expect $a_1 > 0$ and $a_2 = 0$, which would indicate the absence of herding. However, herding would be implied by $a_2 < 0$ which indicates that return dispersions are indeed significantly lower during periods of market stress due to correlated trading behavior which in turn leads to a greater directional similarity in returns. Likewise, $a_2 > 0$ would indicate anti-herding, indicating that traders go against the market consensus (Babalos and Stavroyiannis (2015b)). Equations 4 and 5 are estimated using OLS with robust standard errors.[5] To explore the dynamic properties of herding, we implement one-day rolling regressions first with a 250-day window, and second with a 500-day window.[6]

3.3 Herding and Investor Happiness

Having estimated the herding coefficients a_2 in Equations 4 and 5 using two alternative rolling estimation windows for 250 and 500-days, we next examine the role of investor happiness, as a sentiment proxy, over herding via a linear model of the investor happiness index (Γ_t) and the herding coefficients a_2:

$$a_{2t} = a_0 + a_3\Gamma_t + \epsilon_t \,, \tag{6}$$

where a negative value for a_3 implies a higher (lower) herding tendency in periods of positive (negative) market sentiment (or happiness), and vice versa. Furthermore, considering that financial markets are often characterized by regime-dependent patterns for normal, bullish and bearish market states, we capture the dynamic dependencies in the data by performing a quantile on quantile regression of the herding coefficients and the happiness index. Quantile regressions address the limitations of the standard OLS, which only estimates the mean dependency between the variables. However, as is often the case with financial returns, distribution moments, such as the mean, can be strongly affected by heavy tails (or tail behaviour), non-linearity and extreme values in general (see Koenker (2017)). This is particularly important in the testing of herding, as herding could be characterized as a regime dependent phenomenon in which it is more prevalent

[5] Using the Huber (1967) and White (1982) estimator.

[6] Using the Roll Eviews add-in found at `https://www.eviews.com/Addins/addins.shtml.`

during certain market states like crisis periods or periods of heightened uncertainty when investors feel particularly worried about the direction of their trades.

In response to these limitations, the quantile regression was first introduced by Koenker and Bassett (1978). Koenker (2017) notes that quantile regressions are inherently local and are immune to small deviations in distributions. However, Gupta et al. (2018) note that standard quantile regressions are limited in their ability to capture dependency in its entirety. That is, although quantile regressions capture the relationship between two variables at various points of the conditional distribution, they restrict the possibility that the nature of the independent variable can also influence how the independent variable evolves. The quantile-on-quantile regression (QQR), therefore, offers a more complete picture of the complex dependency structure, and has been utilised in numerous studies in the literature (see Mishra et al. (2019), Chang et al. (2020), and Sim (2016)).

Given this brief explanation on QQR, we follow Sim and Zhou (2015) in postulating the relationship between herding and happiness as follows:

$$a_{2t} = \beta^{\theta}\Gamma_t + \epsilon_t^{\theta}\,, \tag{7}$$

a_{2t} is the θ-quantile of herding where and ϵ_t^{θ} is an error term with a zero-θ. Taking the linear version of $\beta^{\theta}(.)$ with a first order Taylor expansion of $\beta^{\theta}(.)$ around Γ^{τ} gives:

$$\beta^{\theta}(\Gamma_t) \approx \beta^{\theta}(\Gamma^{\tau}) + \beta^{\theta'}(\Gamma^{\tau})(\Gamma_t - \Gamma^{\tau})\,. \tag{8}$$

In this instance both $\beta^{\theta}(\Gamma^{\tau})$ and $\beta^{\theta'}(\Gamma^{\tau})$ are indexed to θ and τ. This means that equation 8 can be summarised as follows:

$$\beta^{\theta}(\Gamma_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(\Gamma_t - \Gamma)\,, \tag{9}$$

and collecting terms gives and substituting into equation 7 :

$$a_{2t} = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(\Gamma^{\tau})(\Gamma_t - \Gamma) + \epsilon_t^{\theta}\,, \tag{10}$$

where $\beta^{\theta}(\Gamma^{\tau})$ and $\beta^{\theta'}(\Gamma^{\tau})$ are substituted with $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)(\Gamma^{\tau})$ respectively.

Therefore, Equation 10 captures the relationship between the θ-quantile of herding in the US foreign exchange market and the τ-quantile of the happiness index, that is, the overall dependence structure of the respective distributions. To this end, to get the estimates of $\hat{\beta}_0(\theta,\tau)$ and $\hat{\beta}_1(\theta,\tau)$ we solve for:

$$\min_{b_0,b_1} \sum_{i=1}^{n} \rho_{\theta}\left[a_{2t} - b_0 - b_1(\widehat{\Gamma}_t - \widehat{\Gamma})\right] K\left(\frac{F_n(\widehat{\Gamma}_t) - \tau}{h}\right)\,, \tag{11}$$

where ρ_{θ} is a tilted absolute value function which produces θ-quantile values of a_{2t}. A Gaussian kernel $K(.)$ is used to weight observations in the neighbourhood of $\widehat{\Gamma^{\tau}}$ using h as a bandwidth. These weights are inversely related to $\widehat{\Gamma}_t - \widehat{\Gamma}$. Lastly, Sim and Zhou (2015) note that the choice of h remains uncertain in kernel regression where if a small h

is chosen the bias of the estimates is smaller but the variance of these estimates increases, and conversely. Similar to Sim and Zhou (2015) we choose a bandwidth of 0.05.

4 Results

4.1 Descriptive Statistics

Table A.1 presents the descriptive statistics including the daily mean and standard deviation, skewness and kurtosis estimates along with the normality tests (Jarque-Bera (JB)), a test for heteroskedasticity (Autoregressive Conditional Heteroskedasticity Lagrange Multiplier (ARCH-LM)), and a test for serial correlation (Ljung-Box (LB)). We observe that the data are leptokurtic with generally high kurtosis values along with mixed skewness estimates (right and left tailed distributions). Also, all time series are typically not normal, justifying the use of the non-linear approach in subsequent tests. Using 10 lags, the ARCH-LM and LB tests indicate the presence of heteroskedasticity in all data series and serial correlation in most. In Table A.2, the unconditional correlations for the US foreign exchange market range from -0.83 (EUR/USD and SEK/USD) to 0.82 (NOK/USD and SEK/USD), while several currencies are found to exhibit low correlation (as low as -0.03 (JPY/USD and AUD/USD).

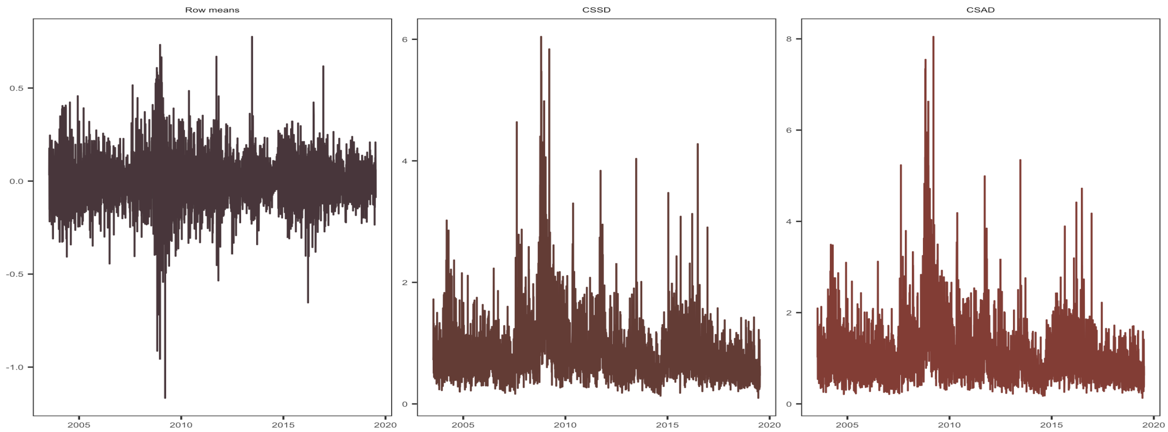
4.2 Static Analysis of Herding

4.2.1 OLS analysis

Figure 1 displays the daily CSSD and CSAD estimates and Table 1 shows the estimates for the quadratic herding model in Equations 4 and 5. Given the positive estimates for the herding coefficient, the quadratic model yields evidence of anti-herding behaviour in the currency market, consistently across both the CSAD and CSSD measures. This is not unexpected as currencies are traded simultaneously at multiple markets and by a wide variety of investor types with heterogeneous beliefs and information sets. However, as shown by Vieira and Pereira (2015), different herding methods can lead to different conclusions. Furthermore, as argued by Christie and Huang (1995) and Chang et al. (2000), amongst others, herding is inherently dynamic and is more prevalent in the time of market stress. Therefore, to capture the possible dynamic nature of herding, we employ rolling regressions and examine whether herding (or otherwise) becomes prevalent during certain market periods.[7]

[7]Other non-linear approaches to herding include Babalos and Stavroyiannis (2015b), Babalos et al. (2015)), and quantile regressions (e.g. Klein (2013)), among others

Figure 1: CSSD and CSAD for the US foreign exchange market



4.2.2 Rolling window analysis

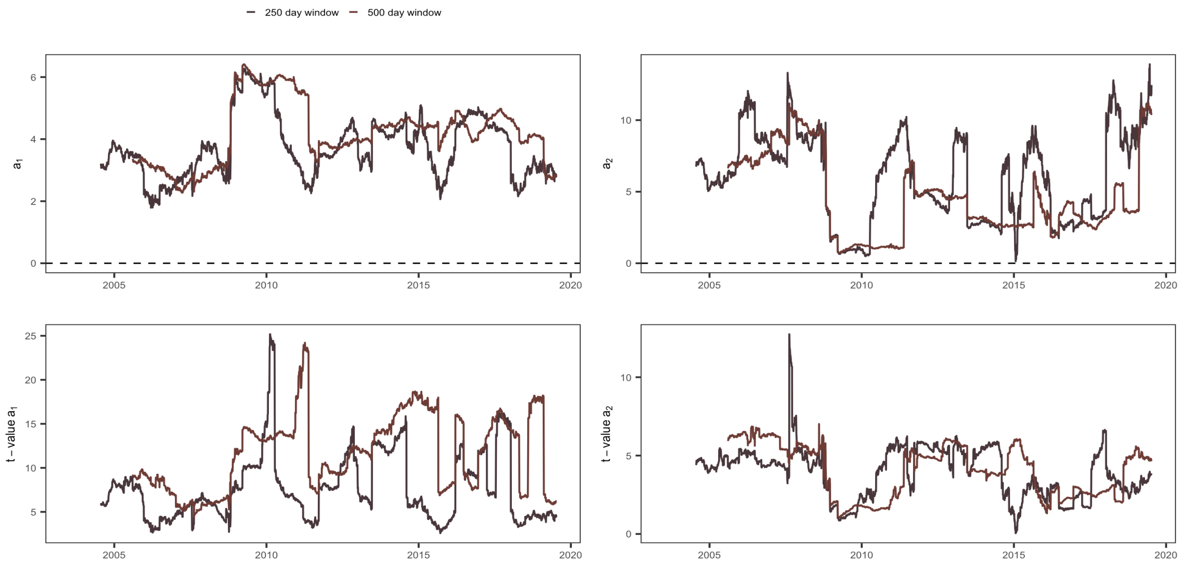
There are no hard and fast rules in determining the size of a window in estimating window regressions. According to Su and Hwang (2009), a short window causes large variations in the estimates obtained, whilst a long window can cause estimates to smooth out and lose idiosyncratic characteristics. In this paper, we follow Babalos et al. (2015) and employ 250 and 500-day windows. Figures 2 and 3 display the estimates obtained from the rolling window analysis based on the CSAD and the CSSD measures, respectively. Consistent with the findings from the static, quadratic model, we find significant evidence of anti-herding across the sample period. Anti-herding is particularly pronounced and highly significant during the financial crisis period (2008-2010), suggesting that the currency market exhibits a markedly different pattern compared to equities for which herding is shown to be more prevalent during crisis periods. Such distinct behavior for currencies could be since these assets are traded at multiple markets and by a wide variety of investors with heterogeneous information sets. Although we observe a brief period in 2005 with negative a_2 estimates, we observe another pronounced period of significant anti-herding post 2015. Accordingly, the rolling window analysis of herding coefficients indicates significant anti-herding tendencies by currency traders, consistently for both measures of cross-sectional dispersion in currency returns with brief periods of herding.

Table 1: Static regression results

Variable	CSAD	CSSD
a_1	4.98(0.0000)	3.78(0.0000)
a_2	2.68(0.0000)	1.85(0.0000)
a_0	0.49(0.0000)	0.42(0.0000)
R-squared	0.77	0.71
Mean dependent var	1.04	0.83
Adjusted R-squared	0.77	0.0.71
S.D. dependent var	0.0.65	0.50
S.E. of regression	0.31	0.0.27
Akaike info criterion	0.51	0.23
Sum squared resid	365.28	276.31
Schwarz criterion	0.52	0.24
Log likelihood	−962.02	−442.92
Hannan-Quinn criter.	0.52	0.24
F-statistic	6263.95	4604.62
Prob(F-statistic)	0.0000	0.0000
Durbin-Watson stat	1.53	1.45
Wald F-statistic	2861.19	1892.36
Prob(Wald F-statistic)	0.0000	0.0000

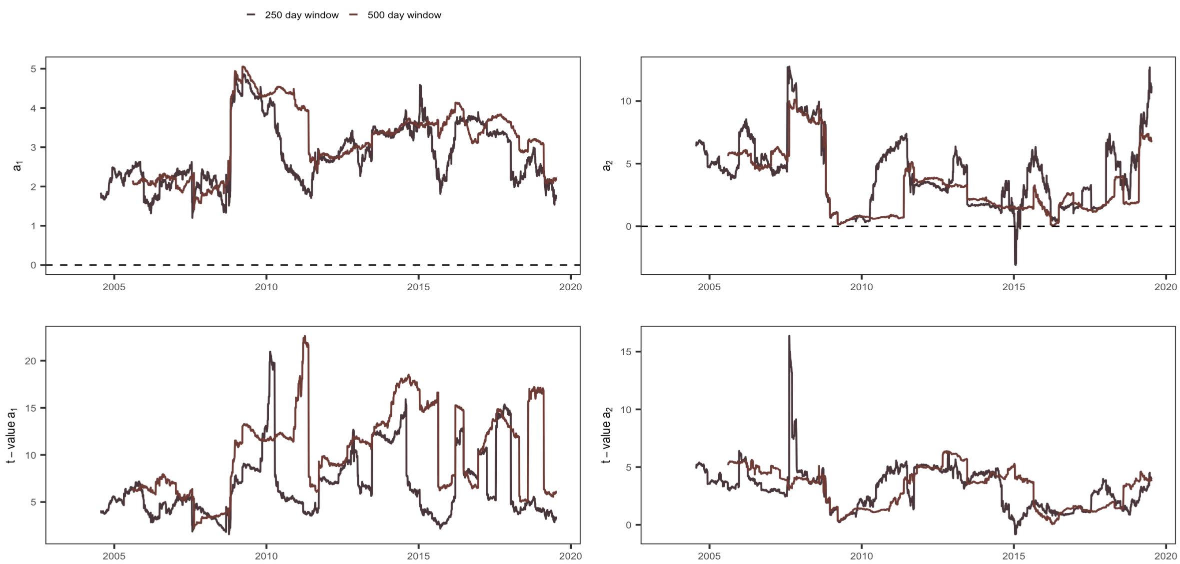
Note: p-values in parentheses.

Figure 2: CSAD rolling regression window analysis of the US foreign exchange market



Note: The black perforated line is used to distinguish between periods of (anti) herding or no herding.

Figure 3: CSSD rolling regression window analysis of the US foreign exchange market



Note: Rolling window results with a_1 (top left)and a_2 (top right) estimates on the top, and the corresponding $t - values$ on the bottom. The black perforated line is used to distinguish between periods of (anti) herding or no herding

4.3 Herding and Investor Happiness Analysis

4.3.1 Static analysis

Examining the role of investor sentiment on herding, the findings for Equation 6, reported in Tables 2 and 3, suggest a negative relationship between investor happiness and anti-herding (negative a_3) in the foreign exchange market, consistently for both CSSD and CSAD measures. That is, positive investor sentiment tends to ease anti-herding by lessening the impact of large price fluctuations on cross-sectional dispersions. In an application to the Portuguese stock market and employing causality analysis, Vieira and Pereira (2015) document weak evidence that herd behaviour is influenced by sentiment. Although the evidence from Portuguese investors suggests a negative relationship between investor sentiment and herding, the evidence from currencies indicate otherwise, suggesting that positive sentiment, in fact, makes anti-herding less severe. Based on this, one can argue that optimistic market conditions create an environment in which traders are more likely to follow the market consensus as the need to do otherwise is less evident. As noted earlier, however, it is possible that the effect of sentiment is rather regime-specific and in order to gain a more comprehensive insight to the dynamic links between sentiment and herding, we proceed with the quantile analysis that allows examining regime-specific dependencies.

4.3.2 QQR analysis

In order to test the dynamic nature of the relationship between herding and investor happiness, we next estimate the quantile-on-quantile regressions (QQR) outlined earlier. Figure 4 shows the results of the QQR estimation, conducted for both herding coefficients obtained from the 250 rolling window analysis. Clearly, the QQR analysis suggests the relationship between investor sentiment and anti-herding is in fact regime specific. During periods of extreme bullish periods, we observe a positive effect of happiness, which means extreme bullish sentiment generally makes anti-herding even stronger. This can also be seen during extreme bearish sentiment when the effect becomes strongly positive. Daviou and Paraschiv (2014) argue that investors do not necessarily lose confidence during extreme increases in risk and instead, they argue, investors build confidence over sharp, subsequent declines in risk. Therefore, it is possible that stronger anti-herding during extreme sentiment states could be due to investors' confidence-building over sharp, subsequent declines in risk.

However, during normal sentiment states, i.e. median happiness quantiles, the effect is found to be negative, which indicates typical sentiment states are associated with less severe anti-herding. Considering that these are the quantiles that represent median or typical values for the happiness index, the negative effect we observe can simply indicate that anti-herding is not necessarily a typical behaviour during normal market conditions, but instead, becomes prevalent during extreme sentiment states driven by sharp fluctuations in risk preferences when investors turn overly confident (extremely positive sentiment) toward their private information or skeptical (extreme negative sentiment) of other traders' information. Nevertheless, the results show that how investor sentiment

Table 2: Herding and investor happiness static analysis (CSAD)

Variable	$a_{2,250}$	$a_{2,500}$
a_3	$-15.09(0.0000)$	$-21.51(0.00000)$
a_0	96.05(0.000)	144.39(0.0000)
R-squared	0.04	0.21
Mean dependent var	5.19	3.50
Adjusted R-squared	0.04	0.21
S.D. dependent var	3.11	2.13
S.E. of regression	3.05	1.89
Akaike info criterion	5.07	4.11
Sum squared resid	23093.05	8872.57
Schwarz criterion	5.07	4.11
Log likelihood	-6281.67	-5096.49
Hannan-Quinn criter.	5.07	4.11
F-statistic	106.69	667.86
Prob(F-statistic)	0.0000	0.0000
Durbin-Watson stat	0.03	0.15
Wald F-statistic	109.43	463.02
Prob(Wald F-statistic)	0.0000	0.000

Note: a_3 is the coefficient for investor happiness index. The regression is implemented with a_2 from the CSSD equations from rolling window analysis. $a_{2,250}$ refers to a_2 from the 250-day window rolling regression and $a_{2,500}$ from the 500-day window rolling regression. p-values in parenthesis.

Table 3: Herding and investor happiness static analysis (CSSD)

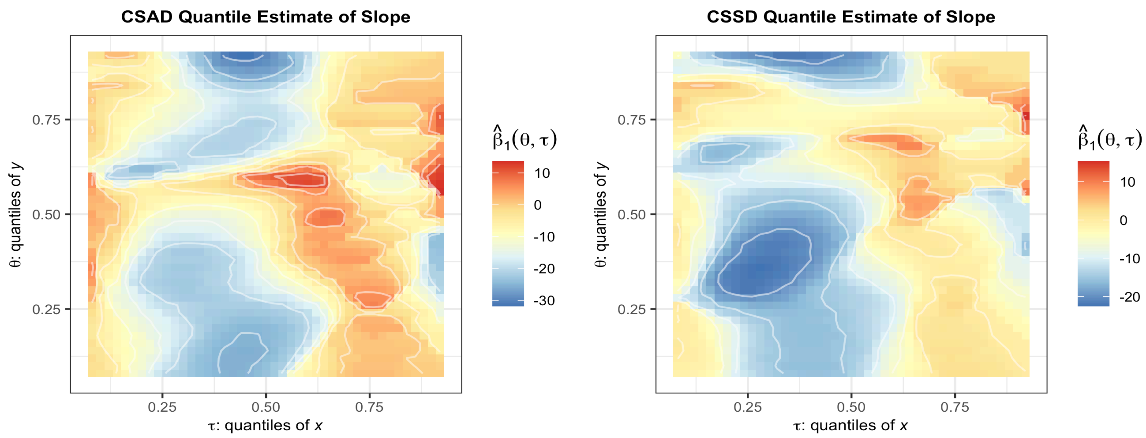
Variable	$a_{2,250}$	$a_{2,500}$
a_3	$-11.52(0.000)$	$-18.83(0.0000)$
a_0	72.55(0.000)	115.53(0.0000)
R-squared	0.04	0.23
Mean dependent var	3.19	2.18
Adjusted R-squared	0.04	0.23
S.D. dependent var	2.30	1.63
S.E. of regression	2.24	1.42
Akaike info criterion	4.45	3.55
Sum squared resid	12526.50	5062.29
Schwarz criterion	4.46	3.55
Log likelihood	-5523.79	-4401.23
Hannan-Quinn criter.	4.46	3.55
F-statistic	114.64	757.61
Prob(F-statistic)	0.0000	0.0000
Durbin-Watson stat	0.03	0.17
Wald F-statistic	108.73	528.02
Prob(Wald F-statistic)	0.0000	0.0000

Note: a_3 is the coefficient for investor happiness index. The regression is implemented with a_2 from the CSSD equations from rolling window analysis. $a_{2,250}$ refers to a_2 from the 250-day window rolling regression and $a_{2,500}$ from the 500-day window rolling regression. p-values in parenthesis.

drives anti-herding behavior depends on the market states that drive sentiment among investors. While the currency market experiences significant anti-herding in general, our analysis shows that extreme investor sentiment (bullish or bearish) has the potential to make such behavior more severe.

The finding that anti-herding is relatively stronger during periods of extreme sentiment is in line with the literature on price cascades (Osler (2005)) and feedback trading (Tayeh and Kallinterakis (2020) and Laopodis (2005)), highlighting the tendency of investors to disregard fundamentals in currency markets and go against the market consensus. Although the results indicate the presence of non-fundamental trading, particularly considering the evidence of feedback trading in currency markets, anti-herding may also be the result of divergence of opinions in terms of information. Such a divergence in opinions could either be due to the difference in the non-fundamental strategies employed by investors (e.g. different investment horizons, predictive models or rules) or due to the variations in the way they interpret their fundamentals. The findings are also in line with the evidence of regime specific herding and anti-herding behaviour documented in the literature. For example, pronounced anti-herding is documented by Tsuchiya (2015) during the financial crisis and quantitative easing periods in the U.S. Similarly, Lin and Lin (2014) find that the herding behaviour of margin traders in the Taiwanese stock market responds to market conditions. In the case of commodities, Demirer et al. (2015), for example, find evidence of herding behaviour only during high volatility states. Nevertheless, our results present novel evidence to the role of sentiment over financial market dynamics, indicating the presence of distinct patterns during extreme and typical sentiment states.

Figure 4: 250 day window herding and investor happiness QQR analysis



5 Conclusion

This paper examines the role of investor sentiment as a driver of herding (or anti-herding) in the currency market. Utilizing daily data from nine advanced market currencies and investor sentiment, proxied by a social media based investor happiness index built on Twitter feed data, we show that the foreign exchange market is generally characterized by strong anti-herding behavior. Utilizing the quantile-on-quantile (QQ) approach, developed by Sim and Zhou (2015), we then show that the relationship between investor sentiment and anti-herding is in fact regime specific, with anti-herding behavior particularly strong during states of extreme investor sentiment. The effect of sentiment on anti-herding is generally stronger in extreme bullish sentiment states, while average sentiment is associated with less severe anti herding. While the findings are generally in line with the evidence in the literature (e.g. Gavriilidis et al. (2016) and Blasco et al. (2018)) that links herding behaviour to extreme events, they also lend support to the behavioral factors for asset pricing models and suggest that real time investor sentiment signals can be utilized to monitor potential speculative activities in the currency market. Considering that currencies are heavily used in arbitrage transactions and in speculative positions, tracing the evolution of anti-herding behavior in these markets is an important consideration as multinational firms rely on the efficiency of exchange rate quotations in their operations as well as the management of exchange rate risks. To that end, our findings can be a good starting point to devise monitoring mechanism in which real time sentiment proxies are used to monitor speculative and anti-herding tendencies among currency traders. Future research can build on our results by examining how real time sentiment proxies drive intraday trades in these markets.

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Appendices

A Data and Summary Statistics

Figure A.1: Currency markets

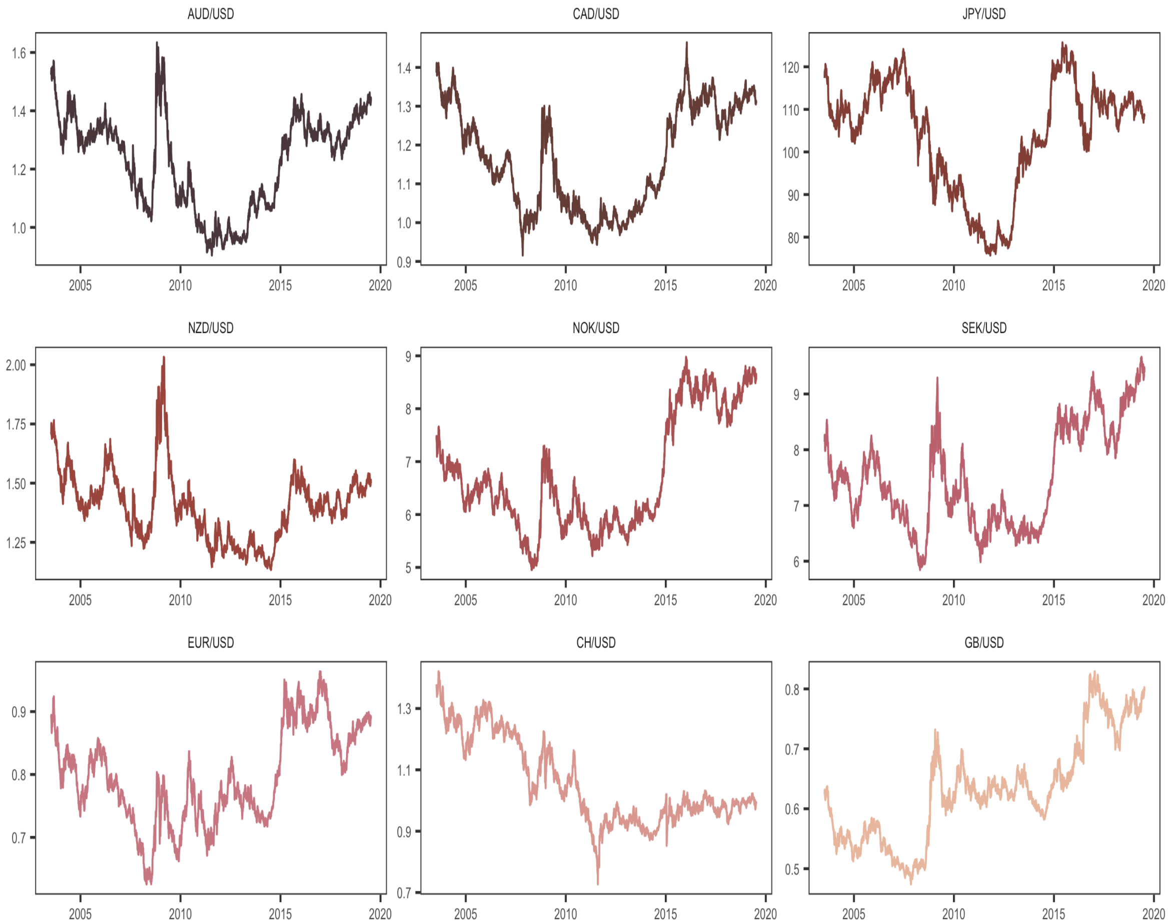

Figure A.2: Currency market returns

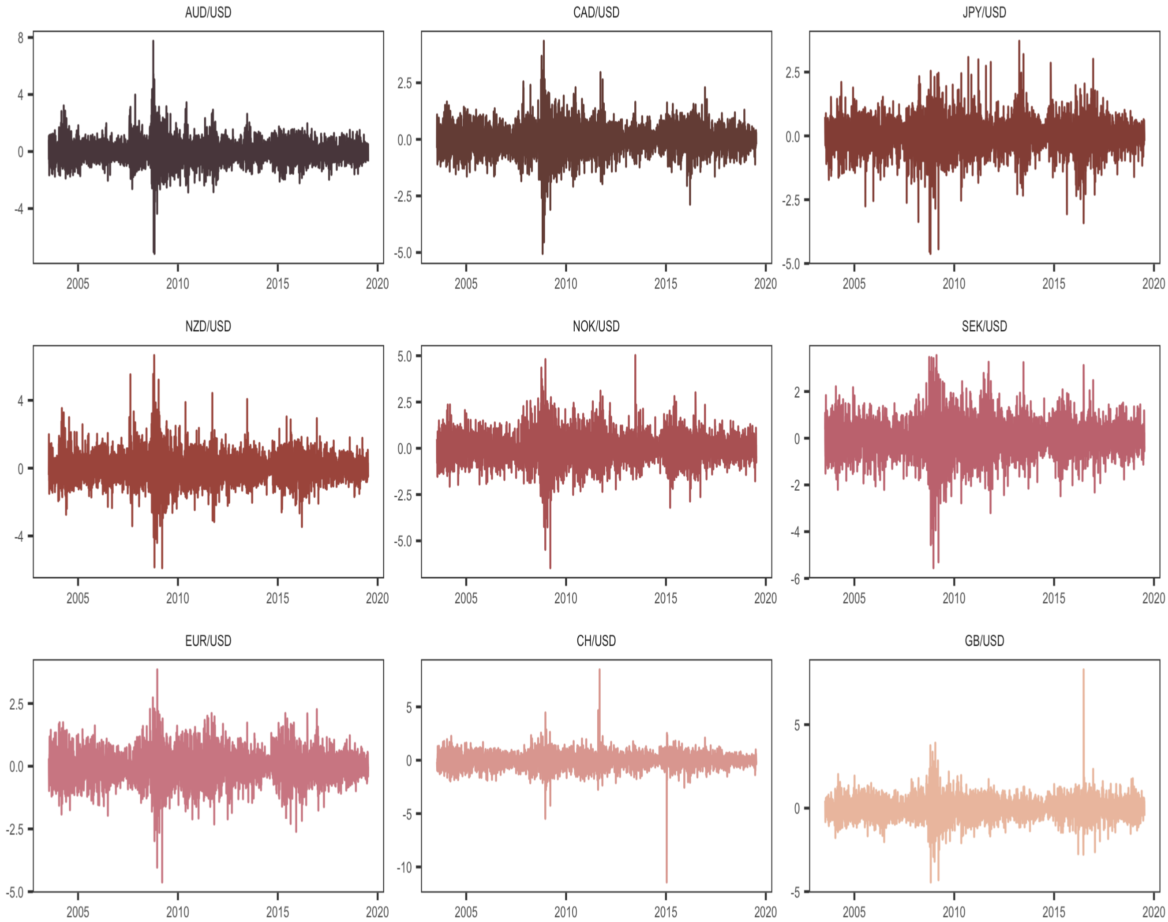

Figure A.3: Investor happiness index

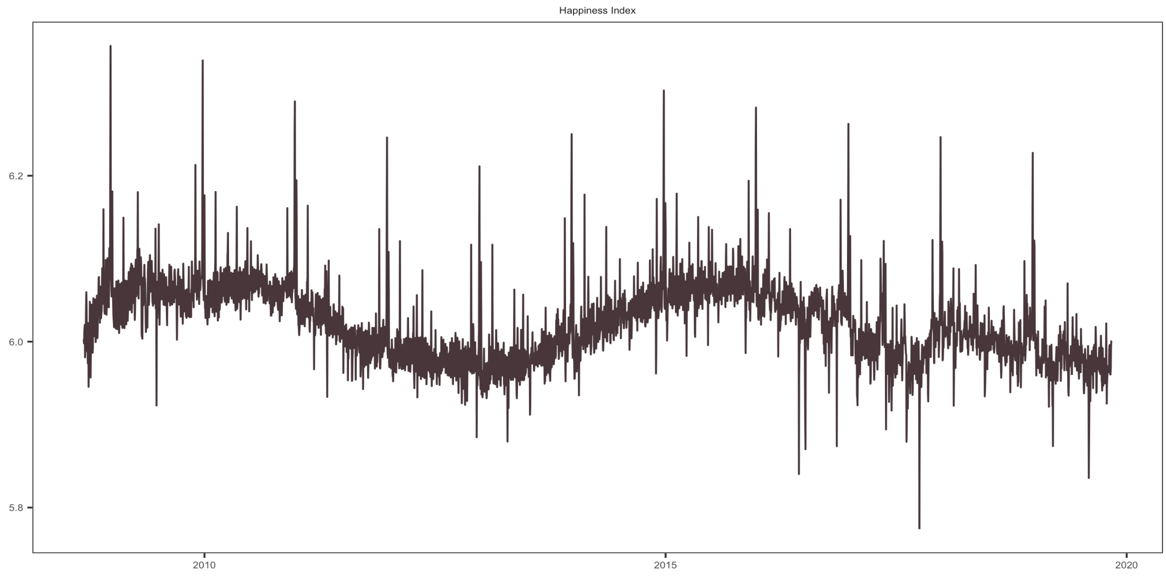

Table A.1: Descriptives statistics

	AUD/USD	CHF/USD	CAD/USD	EUR/USD	GBP/USD	JPY/USD	NOK/USD	NZD/USD	SEK/USD
Mean	−0.002213	−0.007691	0.002835	0.003592	0.008290	−0.005965	0.008653	−0.000375	0.008350
Median	−0.030125	0.019059	0.008339	−0.004473	−0.010487	0.009136	−0.008441	−0.025597	0.006680
Maximum	7.738583	8.478539	4.337515	3.844055	8.287932	3.710207	5.015097	6.645562	3.541090
Minimum	−7.155106	−11.41652	−5.046215	−4.617150	−4.428722	−4.609788	−6.458059	−5.877755	−5.547429
Std. Dev.	0.817106	0.683039	0.614346	0.602709	0.625120	0.638901	0.782316	0.854242	0.763014
Skewness	0.261644	−1.051746	−0.111001	−0.077646	0.671574	−0.174686	0.020088	0.340135	−0.119175
Kurtosis	10.82084	34.66226	7.759811	6.051908	14.61416	6.897811	7.068548	8.211252	6.472129
Jarque-Bera	9520.547	156031.2	3518.342	1447.041	21181.70	2373.185	2565.289	4279.936	1876.931
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARCH-LM (10)	925.55*	504.94*	291.04*	157.24*	501.8*	333.84*	504.93*	196.66*	221.56*
LB (10)	39.97*	29.22*	13.03	8.87	22.71*	15.28	33.48*	14.27	33.61*
Observations	3719	3719	3719	3719	3719	3719	3719	3719	3719

Note: * indicates significance at a 1 per cent level of significance. This table outlines the main descriptive statistics of the data. These include the JB (Jarque-Bera) test for normality, ARCH-LM test for autoregressive conditional heteroskedasticity, and the LB (Ljung Box) test for serial correlation. 10 lags were used for the ARCH-LM and LB tests

Table A.2: Unconditional correlations

	AUD/USD	CAD/USD	EUR/USD	JPY/USD	NZD/USD	NOK/USD	SEK/USD	CHF/USD	GBP/USD
AUD/USD	1	0.3	-0.25	-0.03	0.44	0.31	0.29	-0.15	-0.27
CAD/USD	0.3	1	-0.51	0.01	0.59	0.58	0.55	-0.35	-0.47
EUR/USD	0.25	0.51	1	0.29	0.56	0.78	0.83	-0.75	-0.63
JPY/USD	-0.03	0.01	-0.29	1	0.07	0.16	0.17	-0.4	-0.11
NZD/USD	0.44	0.59	-0.56	0.07	1	0.59	0.58	-0.4	-0.53
NOK/USD	0.31	0.58	-0.78	0.16	0.59	1	0.82	-0.59	-0.58
SEK/USD	0.29	0.55	-0.83	0.17	0.58	0.82	1	-0.61	-0.58
CHF/USD	0.15	0.35	-0.75	0.4	0.4	0.59	0.61	1	-0.47
GBP/USD	0.27	0.47	-0.63	0.11	0.53	0.58	0.58	-0.47	1

B Trade Weights

Figure B.1: Other country trade weights