**University of Pretoria**
*Department of Economics Working Paper Series*

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

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Working Paper: 2020-88
September 2020

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

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September 21, 2020

**Abstract**

This paper investigates (anti) herding in the US foreign exchange market while assessing the role of investor happiness as a predictor of herding. To achieve this objective, it uses dispersion metrics (CSAD and CSSD) and applies OLS regressions with rolling window and quantile-on-quantile regressions (QQR). The results show that the US foreign exchange market is characterized by a strong anti-herding behavior. In normal times, anti-herding and investor happiness are negatively related. However, in extreme bearish and bullish times, investor happiness is associated with more severe anti-herding. The findings are of particular interest to policymakers who are concerned with the stability of the US foreign exchange market.

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

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# 1 Introduction

Classic economic theory indicates that investor decisions are based on rational expectations using all available information in an efficient manner (Scharfstein and Stein (1990)). This is in essence the Efficient Market Hypothesis (EMH) (Fama (1965, 1970)). However, contrary to the EMH, Scharfstein and Stein (1990) points out that professional managers, for example, will 'follow the herd' if concerns about how others will assess their judgments.

Devenow and Welch (1996) in general defines herding as correlated behaviour patterns of individuals such as investor's purchasing similar stocks as a result of either common or independent information. Specifically, herding is defined in terms of its ability to lead to systematic sub-optimal decision making by an entire population of investors resulting in (among others) market bubbles and frenzies. According to Bikhchandani and Sharma (2000), herding increases the fragility of the financial system, and increases volatility in markets.

To this end, the literature distinguishes between rational and irrational herding in explaining herding mechanisms emanating from some price signal. 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)); the principal-agent view which states that managers will act to preserve reputations (see Rajan (1994)); and information cascades were investors substitute private information with inferences about the prior actions of other investors (see Welch (1992)), including the effect of costs associated with information acquisition (Calvo and Mendoza (2000)). Irrational herding views rational decision making amongst investors as a fallacy and is subject to psychological, environmental, and social factors (see Shiller (2000, 2003)).

Empirically, herding is defined in the main as the cross-sectional standard deviation of returns where on average the dispersions measure the proximity of returns to the market mean (Christie and Huang (1995)). According to Christie and Huang (1995) these dispersions are bounded under zero when there is herding (or when returns move with the market return) and will vary from the market return as they increase. Chang et al. (2000) defines the cross-sectional absolute deviation of returns as a dispersions measure instead of the cross-sectional standard deviation of returns.

Herding was studied in stock markets (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 markets (Gleason et al. (2003)), Real Estate Investment Trusts (REITs) (Philippas et al. (2013)), exchange traded funds

(ETFs) (Gleason et al. (2004)), and various commodities markets (Adrangi and Chatrath (2008), Balcilar et al. (2014), Babalos and Stavroyiannis (2015a))). Methodologically, the literature emphasises the dynamic nature of herding through the use of time-varying estimations to in particular understand herding in times of crisis in markets (Balcilar et al. (2013), Babalos and Stavroyiannis (2015a), and Klein (2013)).

The importance of studying herding in foreign exchange rate markets is illuminated by Belke and Setzer (2004). Belke and Setzer (2004) note that in general exchange rate market volatility caused by factors other than changes in fundamental macroeconomic conditions (such as herding) can negatively impact labour market and trade performance, particularly in emerging markets.

Although several studies were conducted in foreign exchange markets, they remain limited in volume and the utilisation of Christie and Huang (1995) and the Chang et al. (2000) definitions of herding. Kim et al. (2004) found evidence of herding in the won-dollar exchange rate market using the power-law approach. Park (2011) found evidence of asymmetric herding in the USD/JPY and USD/KRW markets using Generalised Autoregressive Conditional Heteroskedasticity (GARCH) techniques. Russell (2012) explores how herding informs changes in exchange rate regime choice by the government. Pierdzioch et al. (2012) also found evidence of anti-herding behaviour amongst exchange rate forecasters in emerging markets. Lastly, focusing on the time-varying nature of herding, Tsuchiya (2015) found evidence of herding (anti-herding) over time (including times of crisis) amongst exchange rate forecasters.

In parallel, a number of studies on herding and investor sentiment were conducted (Da et al. (2015), Garcia (2013), Liao et al. (2011), Bathia and Bredin (2013), Gavriilidis et al. (2016), and Blasco et al. (2018)). For example, amongst others, Vieira and Pereira (2015) found weak evidence of a relationship between herding and investor sentiment in small European markets. Gavriilidis et al. (2016) showed that herding was stronger within the Ramadan period where investor optimism is enhanced than in periods outside of Ramadan. In the UK, Blasco et al. (2018) found that herding increased in periods of market stress when analysts are forced to release negative information in periods of pronounced investor sentiment. The evidence on the relationship between herding and investor sentiment is varied and evolving. As shown above, psychological factors are thought to explain herding.

In this paper, we investigate herding in the US foreign exchange market using ordinary least squares with rolling window regressions, and quantile-on-quantile regressions (in order to the capture entirety of the dependency structure). Notably, we propose the investor happiness index as a predictor of herding in the US foreign exchange market.

Next, we discuss the data and methodology outlining the herding model, the econometric methods (ordinary least squares regressions with rolling windows), and the herding and investor happiness model. This is followed by a discussion of the results, then we draw some conclusions.

# 2 Data and Methodology

## 2.1 Data

We focus on nine exchange rate markets as shown in Figure A.1 in Appendix A, with the USD as the common denominator. The markets are Australia (AUD), Canada (CAD), the European Union (EUR), Japan (JPY), New Zealand (NZD), Norway (NOK), Sweden (SEK), Switzerland (CHF), and the United Kingdom (GBP). The daily exchange rate data was sourced from the Global Financial Database[1]. After accounting for missing data our sample ranged from 2003-07 to 2019-07.

The trade weight data were sourced from the Bank of International Settlements[2] (BIS). The BIS data are available in three-year intervals from 1990 to 2016. These were converted to a daily frequency by assuming the daily trade weights do not deviation from the three-year weights. The daily trade weights are shown in Figure B.1 in Appendix B. We calculate market returns using the exchange rates in the following manner:

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

where $R_t$ is a return at time $t$, $E_t$ and $E_{t-1}$ is the exchange rate at time $t$ and $t-1$. The returns for the exchange rates are shown in Figure A.2 in Appendix A.

Recently, Bonato et al. (2020) outline the importance of investor happiness in explaining the first and second moments in stock markets. Given this, investor happiness can be 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)).

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 also been used. However, Da et al. (2015) underscores the move in the literature toward non-market high-frequency measures. Given that market-based measures are available at a high frequency, they can reflect more than just investor sentiment. Da et al. (2015) underscores this point by creating the Financial and Economic Attitudes Revealed by Search (FEARS) index.

[1] https://www.globalfinancialdata.com
[2] https://www.bis.org/statistics/eer.htm

Therefore, in line with Da et al. (2015) and others, we use the investor happiness index[3], a non-market based index, which measures investor happiness based on Twitter user-generated data. This is not without a precedent in the literature (see Sibley et al. (2016), Reboredo and Ugolini (2018), and You et al. (2017)). The investor happiness index is shown in Figure A.3.

## 2.2 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 used the respective trade weight of each market with the US (see Xie et al. (2015)). These are calculated for all the 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 stock 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 $\sum_i w_{i,t} = 1$.

Continuing with Chang et al. (2000) equations 4 and 5 postulate a relationship between the CSSD and $R_{m,t}$ and the $R^2_{m,t}$ which indicates that higher investor risk is associated with higher returns. We follow the same logic with the CSAD:

[3]https://hedonometer.org/timeseries/en_all/

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

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

In the absence of herding we expect that $a_1 > 0$ and $a_2 = 0$. Herding is present when $a_2 < 0$ which indicates that the standard deviations of returns decline in periods of market stress, and anti-herding is present when $a_2 > 0$ (Babalos and Stavroyiannis (2015b)).

Equations 4 and 5 are estimated using OLS with robust standard errors[4]. 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[5].

## 2.3 Herding and Investor Happiness Model

Based on the results on the presence of (anti) herding using $CSSD_t$ or $CSAD_t$, we estimate a linear relationship between the investor happiness index ($\Gamma_t$) and the rolling window regressions estimated $a_2$ from equations 4 or 5 using ordinary least squares (OLS) (static and rolling) for the 250 and 500-day windows:

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

where a positive relationship signals higher/lower levels of herding in periods of positive/negative market sentiment (or happiness), and vice versa. In essence, the question to answer is, do periods of positive/negative market sentiment explain periods of market herding?

To further capture the dynamic dependencies in the data, we perform a quantile on quantile regressions. Quantile regressions address the limitations of OLS which only estimates the mean dependency between on or more independent variables and the dependant variable. 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)). 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.

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

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

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 variable (for example) at various points of the conditional distribution, it restricts the possibility that the nature of the independent variable can also influence how the independent variable is calculated. The quantile-on-quantile regression (QQR), therefore, offers a more complete picture of the complex dependency structure, and was utilised numerous times 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 $\theta$-quantile of herding where and $\epsilon_t^{\theta}$ is an error term with a zero-$\theta$. Taking the linear version of $\beta^{\theta}(.)$ with a first order Taylor expansion of $\beta^{\theta}(.)$ around $\Gamma^{\tau}$ 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 $\theta$ and $\tau$. 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 $\theta$-quantile of herding in the US foreign exchange market and the $\tau$-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 $\rho_\theta$ is a tilted absolute value function which produces $\theta$-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.

# 3 Results

## 3.1 Descriptive Statistics

The descriptive statistics are shown in Table A.1. The daily percentage mean and standard deviation, Skewness and Kurtosis coefficients, 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)) are reported.

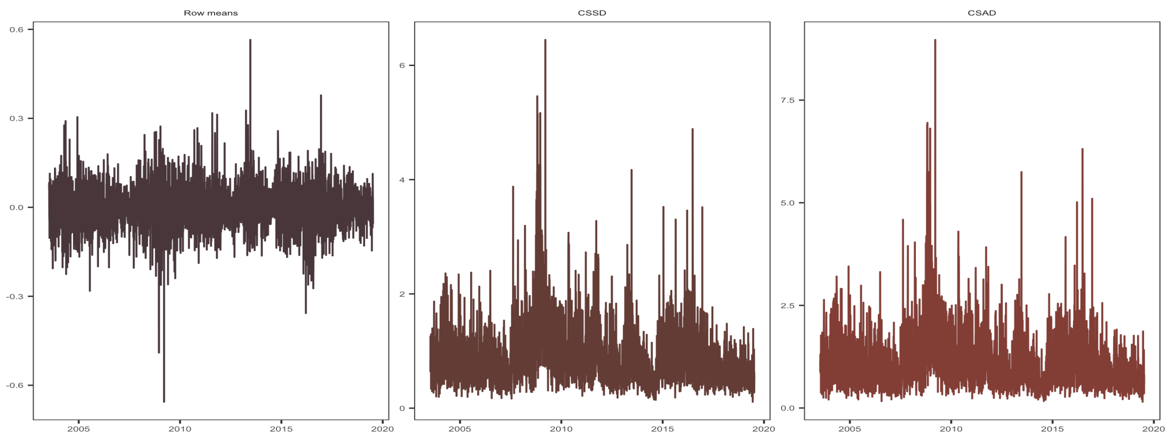
The data are leptokurtic with, in the main, high kurtosis statistics with mixed skewness (right and left tailed distributions). Also, all the time series are typically not normal. Using 10 lags, the ARCH-LM and LB tests indicate the presence of heteroskedasticity in all the data and serial correlation in some most of the data. In Table A.2 the unconditional correlations for the US foreign exchange market range from -0.83 (USD/EUR and SEK/USD) to 0.82 (NOK/USD and SEK/USD). However. some correlations are low (as low as -0.03 (JPY/USD and AUD/USD).

## 3.2 Static Analysis of Herding

### 3.2.1 OLS analysis

The CSSD and CSAD for the US foreign exchange market are shown in Figure 1. Table 1 shows all the regression coefficients of the non-linear equations 4 and 5. We find evidence of anti-herding behaviour with both the CSAD and CSSD. However, as shown by Vieira and Pereira (2015), different herding methods can lead to different conclusions. Therefore, we implemented rolling window regressions in the next sessions.

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




Various reasons for using multiple methods have been advanced in the literature. For example, as shown 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, time-varying techniques may be more relevant. Other authors used rolling regressions (for example Babalos and Stavroyiannis (2015b) and Stavroyiannis and Babalos (2017)), and quantile regressions (for example Klein (2013)), amongst other approaches.

### 3.2.2 Rolling window analysis

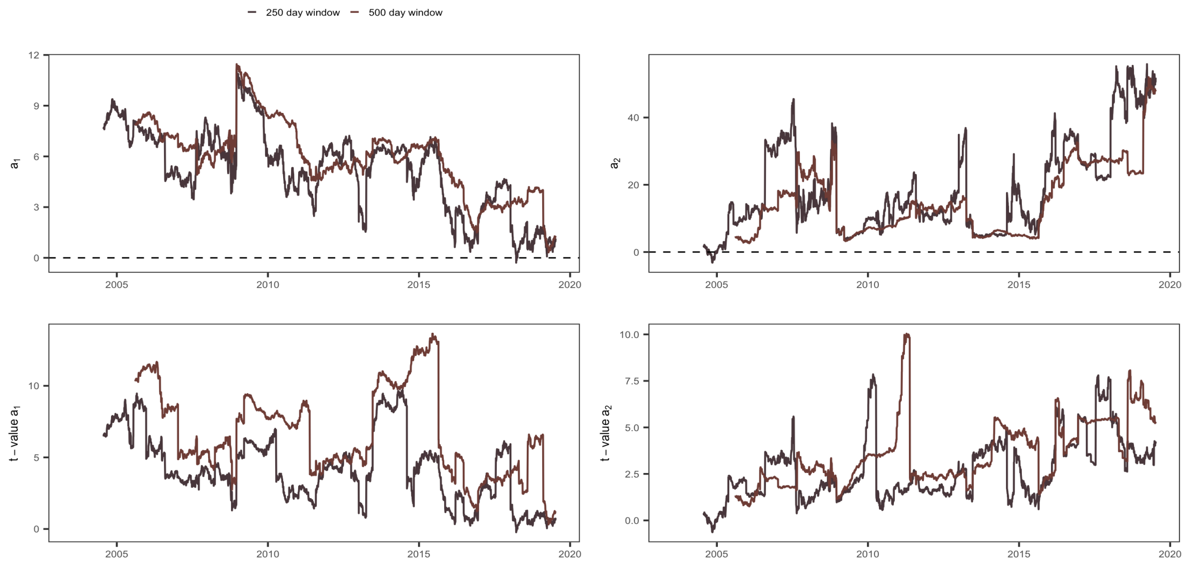
There are no hard and fast rules in determining the size of a window in estimating window regressions. According to Su and Hwang (2009) a short window causes large variations in estimates, whilst a long window can cause estimates to smooth out and lose idiosyncratic characteristics. These challenges continue in the literature. In this paper, we follow others such as Stavroyiannis and Babalos (2017) with 250 and 500-day windows.

Table 1: Static regression results

| Variable | CSAD | CSSD |
|---|---|---|
| $a_1$ | 7.31(0.0000) | 5.70(0.0000) |
| $a_2$ | 9.04(0.0000) | 5.96(0.0000) |
| $a_0$ | 0.6325(0.0000) | 0.5278(0.0000) |
| R-squared | 0.4642 | 0.4434 |
| Mean dependent var | 1.05 | 0.8553 |
| Adjusted R-squared | 0.4639 | 0.4431 |
| S.D. dependent var | 0.6700 | 0.5150 |
| S.E. of regression | 0.4905 | 0.3843 |
| Akaike info criterion | 1.41 | 0.9264 |
| Sum squared resid | 894.30 | 549.05 |
| Schwarz criterion | 1.41 | 0.9314 |
| Log likelihood | −2626.93 | −1719.79 |
| Hannan-Quinn criter. | 1.41 | 0.9282 |
| F-statistic | 1610.06 | 1480.21 |
| Prob(F-statistic) | 0.0000 | 0.0000 |
| Durbin-Watson stat | 1.49 | 1.33 |
| Wald F-statistic | 753.71 | 688.49 |
| Prob(Wald F-statistic) | 0.0000 | 0.0000 |

Note: p-values in parentheses.

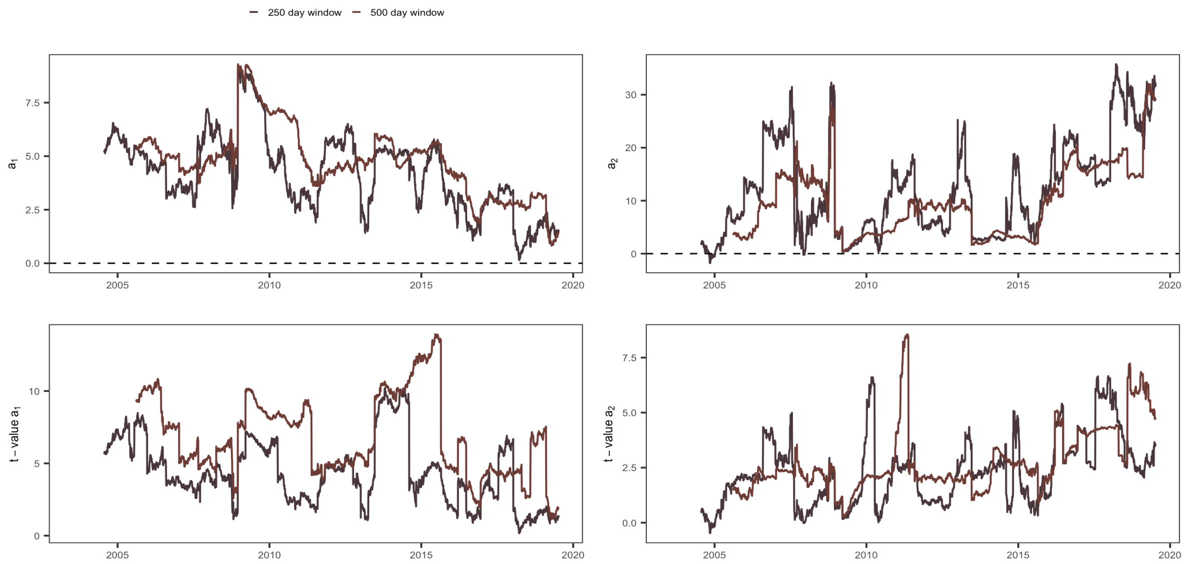
Figure 2: CSAD rolling regression window analysis of the US foreign exchange market




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

As shown in Figures 2 and 3 we perform a rolling window analysis with the CSAD and the CSSD. We find significant evidence of anti-herding. Anti-herding is particularly pronounced and highly significant in the financial crisis period (2008-2010). There was a brief period of herding in 2005 (negative $a_2$). Post-2015, we observe another pronounced period of significant anti-herding. The rolling window analysis with both measures (CSSD and CSAD), therefore, tells the same story of mainly anti-herding with brief periods of 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

## 3.3 Herding and Investor Happiness Analysis

### 3.3.1 Static analysis

Implementing equation 6 reveals that in the main the relationship between investor happiness and anti-herding (positive $a_2$) in the US foreign exchange market was negative (negative $a_3$) for CSSD and CSAD. This is shown in Tables 2 and 3. That is a positive investor sentiment decreases anti-herding. However, the CSAD results revealed more significant estimates at higher magnitudes. This negative relationship consistent with Vieira and Pereira (2015) who also found a negative relationship between investor sentiment and herding.

### 3.3.2 QQR analysis

To test the dynamic nature of the relationship between herding and investor happiness we estimate a QQR. Figure 4 shows the results of the QQR estimation. This was conducted for both herding measures at the 250 herding window. Figure 4 in particular shows a strong negative relationship between anti-herding and investor happiness at the 50th percentile of the happiness index. We see this negative relationship to varying degrees at all quantiles of anti-herding up to the median, of the happiness index. After the happiness index median the relationship tends to be positive. In particular, at

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

| Variable | $a_{2,250}$ | $a_{2,500}$ |
|---|---|---|
| $a_3$ | −84.49(0.0000) | −93.10(0.00000) |
| $a_0$ | 528.45(0.000) | 575.79(0.0000) |
| R-squared | 0.0605 | 0.1268 |
| Mean dependent var | 19.93 | 15.49 |
| Adjusted R-squared | 0.0601 | 0.1265 |
| S.D. dependent var | 14.41 | 10.97 |
| S.E. of regression | 13.97 | 10.25 |
| Akaike info criterion | 8.1132 | 7.4945 |
| Sum squared resid | 483561.7 | 260487.8 |
| Schwarz criterion | 8.11 | 7.49 |
| Log likelihood | −10050.28 | −9283.80 |
| Hannan-Quinn criter. | 8.11 | 7.49 |
| F-statistic | 159.61 | 359.72 |
| Prob(F-statistic) | 0.0000 | 0.0000 |
| Durbin-Watson stat | 0.0439 | 0.0834 |
| Wald F-statistic | 180.04 | 342.31 |
| 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)

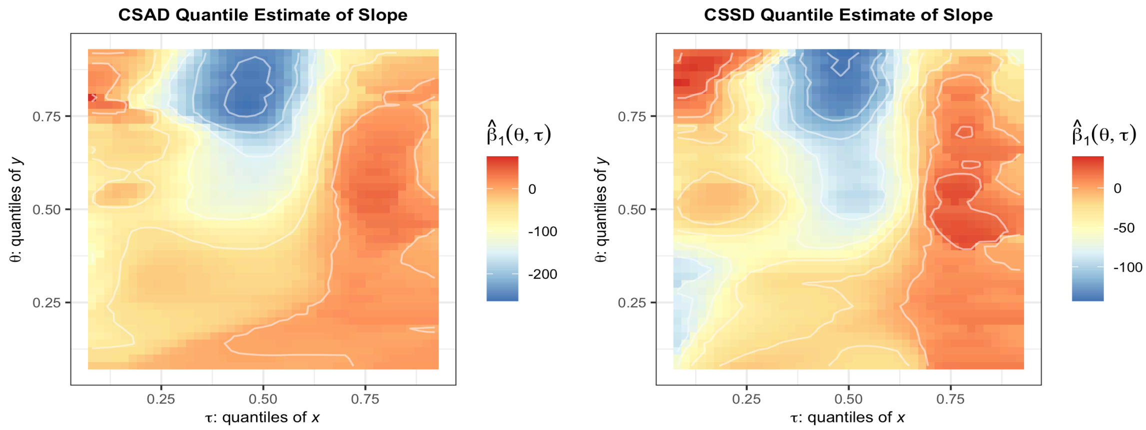
| Variable | $a_{2,250}$ | $a_{2,500}$ |
|---|---|---|
| $a_3$ | −50.85(0.000) | −63.98(0.0000) |
| $a_0$ | 318.62(0.000) | 394.77(0.0000) |
| R-squared | 0.0547 | 0.1394 |
| Mean dependent var | 12.58 | 9.70 |
| Adjusted R-squared | 0.0543 | 0.1390 |
| S.D. dependent var | 9.12 | 7.19 |
| S.E. of regression | 8.87 | 6.67 |
| Akaike info criterion | 7.20 | 6.63 |
| Sum squared resid | 194823.5 | 110326.7 |
| Schwarz criterion | 7.20 | 6.64 |
| Log likelihood | −8923.92 | −8219.36 |
| Hannan-Quinn criter. | 7.20 | 6.63 |
| F-statistic | 143.49 | 401.16 |
| Prob(F-statistic) | 0.0000 | 0.0000 |
| Durbin-Watson stat | 0.0440 | 0.095 |
| Wald F-statistic | 169.63 | 389.14 |
| 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.

the 75th percentile of the happiness index, we see clear evidence of a positive relationship.

This picture is consistent with the CSAD and CSSD. However, with the CSSD we see evidence of the negative relationship at the highest percentiles. Both measures also show a slight positive relationship at the lowest percentile of the happiness index and the higher percentiles of herding.

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




Overall the QQR results confirm the OLS results that the relationship between anti-herding and happiness is mainly negative. The results suggest that overall the relationship between anti-herding and investor happiness is regime specific. That is, in extreme bullish periods, positive investor sentiment leads to stronger anti-herding, and this can also be seen in extreme bearish periods. However, in normal times (or at the median) investor happiness is associated with less severe anti-herding.

# 4 Conclusion

We sought to investigate herding in the US foreign exchange market and to understand investor happiness as a predictor. This was achieved using the two dispersion metrics of investor risk (CSSD and CSAD) which were estimated using OLS, regression with rolling windows, and QQR. A scan of the literature suggests that this may be the first time these metrics have been utilised in the US foreign exchange market. After confirming the presence of herding, the relationship between herding and investor happiness was estimated using OLS with rolling windows.

Using the OLS and rolling window analysis, anti-herding is found to be significant in the US foreign exchange market. There were no differences in the rolling window the results due to the two measures of herding. It is worth noting that in the periods of market stress, anti-herding was pronounced adding to the evidence that the US foreign exchange market is in the main inline with the EMH.

The results on the role of investor happiness in explaining herding in the US foreign exchange market suggest a strong negative relationship between anti-herding and happiness. This was supported by the OLS and QQR analyses. That is, the higher the level of investor happiness the lower the anti-herding in normal times. However, in extreme bullish and bearish times, investor happiness is associated with more severe anti-herding. This is well in line with others in the literature (see Gavriilidis et al. (2016) and Blasco et al. (2018)). That is, herding behaviour in the US foreign exchange market is linked to extreme events on both sides of the happiness coin. This should, in particular, be of interest to policymakers as they seek to respond to crises.

# References


Adrangi, B. and Chatrath, A. (2008). Do commodity traders herd. *Financial Review*, 43(3):461–476.

Babalos, V. and Stavroyiannis, S. (2015a). Herding, anti-herding behaviour in metal commodities futures: A novel portfolio-based approach. *Applied Economics*, pages 1–15.

Babalos, V. and Stavroyiannis, S. (2015b). On the time varying nature of herding behaviour: Evidence from major European indices. *Global Business and Economics Review*, 17(3):298–309.

Balcilar, M., Demirer, R., and Hammoudeh, S. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. *Journal of International Financial Markets, Institutions and Money*, 23:295–321.

Balcilar, M., Demirer, R., and Hammoudeh, S. (2014). What drives herding in oil-rich, developing stock markets? Relative roles of own volatility and global factors. *The North American Journal of Economics and Finance*, 29:418–440.

Bathia, D. and Bredin, D. (2013). An examination of investor sentiment effect on G7 stock market returns. *The European Journal of Finance*, 19(9):909–937.

Belke, A. and Setzer, R. (2004). Contagion, herding and exchange-rate instability: A survey. *Intereconomics*, 39(4):222–228.

BenSada, A. (2017). Herding effect on idiosyncratic volatility in U.S. industries. *Finance Research Letters*, 23:121–132.

Bikhchandani, S. and Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers*, 47(3):279–310.

Blasco, N., Corredor, P., and Ferrer, E. (2018). Analysts herding: When does sentiment matter? *Applied Economics*, 50(51).

Bonato, M., Gkillas, K., Gupta, R., and Pierdzioch, C. (2020). A note on investor happiness and the predictability of realized volatility of gold. Working Papers 202004, University of Pretoria, Department of Economics.

Brown, G. W. and Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, 11(1):1–27.

Calvo, G. A. and Mendoza, E. G. (2000). Rational contagion and the globalization of securities markets. *Journal of International Economics*, 51(1):79–113.

Chang, B. H., Sharif, A., Aman, A., Suki, N. M., Salman, A., and Khan, S. A. R. (2020). The asymmetric effects of oil price on sectoral islamic stocks: New evidence from quantile-on-quantile regression approach. *Resources Policy*, 65:101571.

Chang, E. C., Cheng, J. W., and Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10):1651–1679.

Chiang, T. C. and Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, 34(8):1911–1921.

Christie, W. G. and Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal*, 51(4):31–37.

Da, Z., Engelberg, J., and Gao, P. (2015). The sum of all FEARS: Investor sentiment and asset prices. *The Review of Financial Studies*, 28(1):1–32.

Demirer, R. and Kutan, A. M. (2006). Does herding behavior exist in Chinese stock markets? *Journal of International Financial Markets, Institutions and Money*, 16(2):123–142.

Demirer, R., Kutan, A. M., and Chen, C.-D. (2010). Do investors herd in emerging stock markets?: Evidence from the Taiwanese market. *Journal of Economic Behavior & Organization*, 76(2):283–295.

Devenow, A. and Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40(3-5):603–615.

Dow, J. and Gorton, G. (1994). Arbitrage chains. *The Journal of Finance*, 49(3):819–849.

Economou, F., Katsikas, E., and Vickers, G. (2016). Testing for herding in the Athens stock exchange during the crisis period. *Finance Research Letters*, 18:334–341.

Economou, F., Kostakis, A., and Philippas, N. (2011). Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money*, 21(3):443–460.

Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, 38(1):34–105.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2):383–417.

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance*, 68(3).

Gavriilidis, K., Kallinterakis, V., and Tsalavoutas, I. (2016). Investor mood, herding and the Ramadan effect. *Journal of Economic Behavior & Organization*, 132.

Gebka, B. and Wohar, M. E. (2013). International herding: Does it differ across sectors? *Journal of International Financial Markets, Institutions and Money*, 23:55–84.

Gleason, K. C., Lee, C. I., and Mathur, I. (2003). Herding behavior in European futures markets. *Finance Letters*, (1):4–5.

Gleason, K. C., Mathur, I., and Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. *Journal of Empirical Finance*, 11(5):681–694.

Gupta, R., Pierdzioch, C., Selmi, R., and Wohar, M. E. (2018). Does partisan conflict predict a reduction in us stock market (realized) volatility? evidence from a quantile-on-quantile regression model. *The North American Journal of Economics and Finance*, 43:87–96.

Hirshleifer, D., Subrahmanyam, A., and Titman, S. (1994). Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance*, 49(5):1665–1698.

Huber, P. J. (1967). The behavior of maximum likelihood estimates under nonstandard conditions. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, volume 1, pages 221–233. University of California Press.

Kim, K., Yoon, S.-M., and Kim, Y. (2004). Herd behaviors in the stock and foreign exchange markets. *Physica A*, (341):536–532.

Klein, A. C. (2013). Time-variations in herding behavior: Evidence from a markov switching SUR model. *Journal of International Financial Markets, Institutions and Money*, 26:291–304.

Koenker, R. (2017). Quantile regression: 40 years on. *Annual Review of Economics*, 9:155–176.

Koenker, R. and Bassett, G. (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, pages 33–50.

Kremer, S. and Nautz, D. (2013). Causes and consequences of short-term institutional herding. *Journal of Banking & Finance*, 37(5):1676–1686.

Lao, P. and Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics*, 22(6):495–506.

Liao, T.-L., Huang, C.-J., and Wu, C.-Y. (2011). Do fund managers herd to counter investor sentiment? *Journal of Business Research*, 64(2).

Mishra, S., Sharif, A., Khuntia, S., Meo, M. S., and Khan, S. A. R. (2019). Does oil prices impede islamic stock indices? fresh insights from wavelet-based quantile-on-quantile approach. *Resources Policy*, 62:292–304.

Mobarek, A., Mollah, S., and Keasy, K. (2014). A cross-country analysis of herd behaviour in Europe. *Journal of International Financial Markets, Institutions, and Money*, 32 (2014):102–127.

Park, B.-J. (2011). Asymmetric herding as a source of asymmetric return volatility. *Journal of Banking & Finance*, 35(10):2657–2665.

Philippas, N., Economou, F., Babalos, V., and Kostakis, A. (2013). Herding behavior in REITs: Novel tests and the role of financial crisis. *International Review of Financial Analysis*, 29:166–174.

Pierdzioch, C., Rlke, J.-C., and Stadtmann, G. (2012). A note on forecasting emerging market exchange rates: Evidence of anti-herding. *Review of International Economics*, 20(5):974–984.

Rajan, R. G. (1994). Why bank credit policies fluctuate: A theory and some evidence. *The Quarterly Journal of Economics*, 109(2):399–441.

Reboredo, J. C. and Ugolini, A. (2018). The impact of Twitter sentiment on renewable energy stocks. *Energy Economics*, 76:153–169.

Russell, J. (2012). Herding and the shifting determinants of exchange rate regime choice. *Applied Economics*, 44(32):4187–4197.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, pages 465–479.

Shiller, R. J. (2000). *Irrational exuberance*. Princeton University.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, 17(1):83–104.

Sibley, S. E., Wang, Y., Xing, Y., and Zhang, X. (2016). The information content of the sentiment index. *Journal of Banking & Finance*, 62:164–179.

Sim, N. (2016). Modeling the dependence structures of financial assets through the copula quantile-on-quantile approach. *International Review of Financial Analysis*, 48:31–45.

Sim, N. and Zhou, H. (2015). Oil prices, us stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, 55:1–8.

Stavroyiannis, S. and Babalos, V. (2017). Herding, faith-based investments and the global financial crisis: Empirical evidence from static and dynamic models. *Journal of Behavioral Finance*, 18(4):478–489.

Su, Y. and Hwang, J.-S. (2009). A two-phase approach to estimating time-varying parameters in the capital asset pricing model. *Journal of Applied Statistics*, 36(1):79–89.

Tan, L., Chiang, T. C., Mason, J. R., and Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal*, 16(1-2):61–77.

Tsuchiya, Y. (2015). Herding behavior and loss functions of exchange rate forecasters over interventions and financial crises. *International Review of Economics & Finance*, 39:266–276.

Venezia, I., Nashikkar, A., and Shapira, Z. (2011). Firm specific and macro herding by professional and amateur investors and their effects on market volatility. *Journal of Banking & Finance*, 35(7):1599–1609.

Vieira, E. F. S. and Pereira, M. S. V. (2015). Herding behaviour and sentiment: Evidence in a small European market. *Revista de Contabilidad*, 18(1).

Welch, I. (1992). Sequential sales, learning, and cascades. *The Journal of Finance*, 47(2):695–732.

White, H. (1982). Maximum likelihood estimation of misspecified models. *Econometrica: Journal of the Econometric Society*, pages 1–25.

Xie, T., Xu, Y., and Zhang, X. (2015). A new method of measuring herding in stock market and its empirical results in chinese a-share market. *International Review of Economics & Finance*, 37:324–339.

You, W., Guo, Y., and Peng, C. (2017). Twitter's daily happiness sentiment and the predictability of stock returns. *Finance Research Letters*, 23:58–64.

# Appendices

## A Data and Summary Statistics

Figure A.1: Currency markets

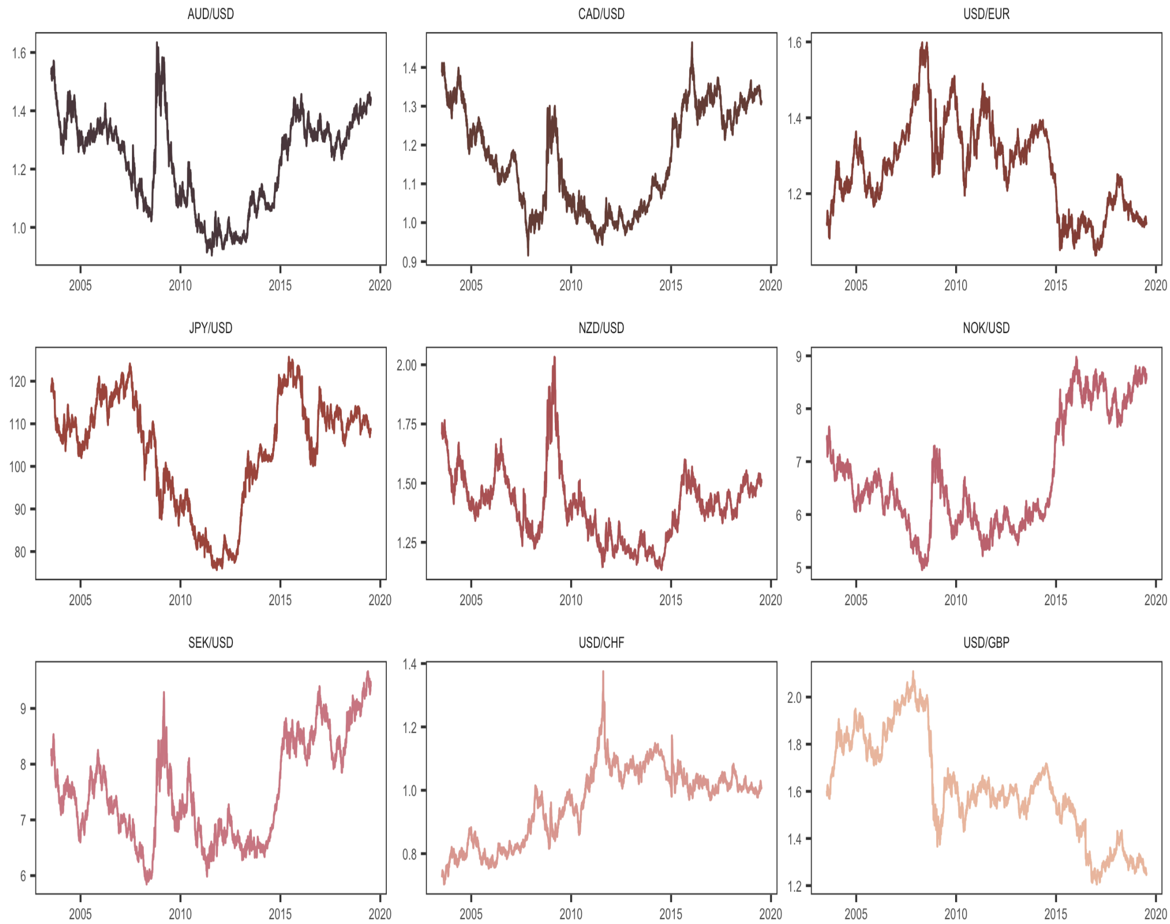


Figure A.2: Currency market returns

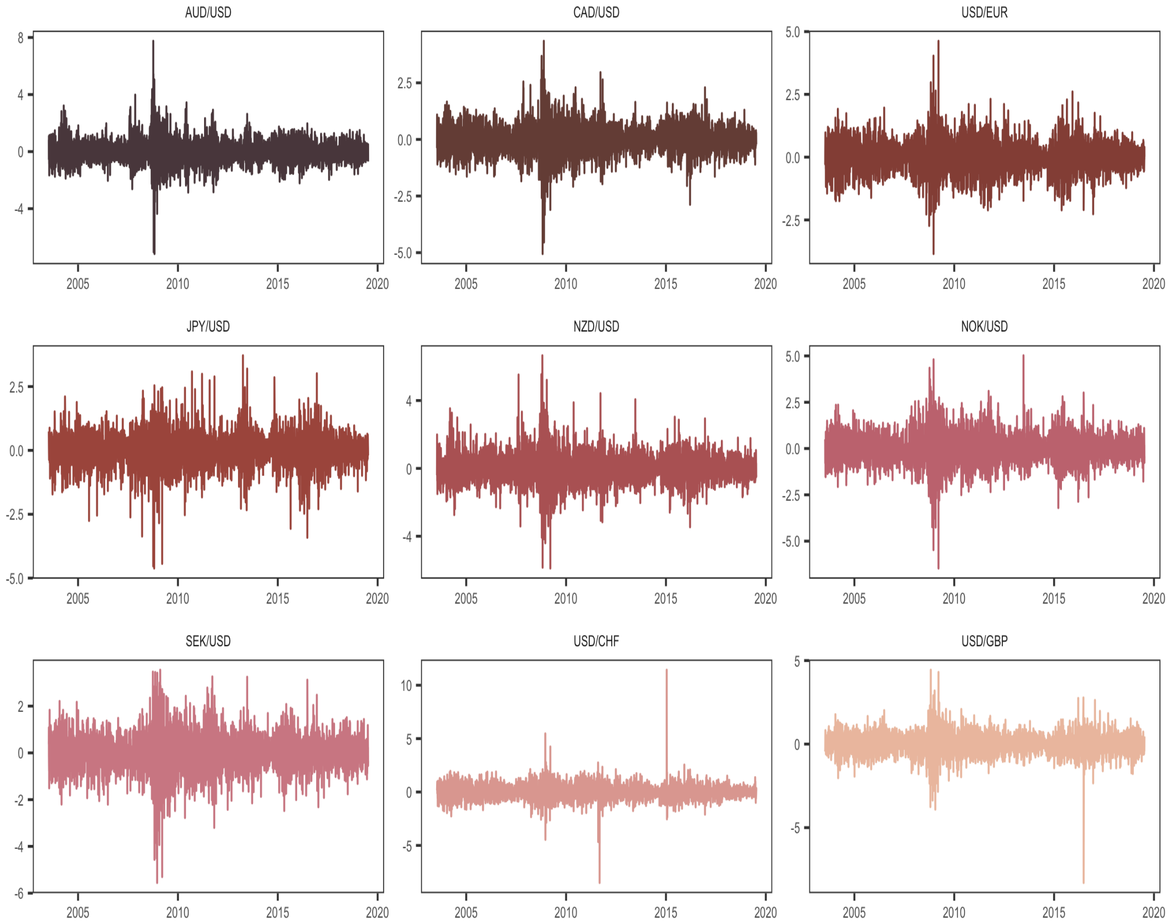


Figure A.3: Investor happiness index

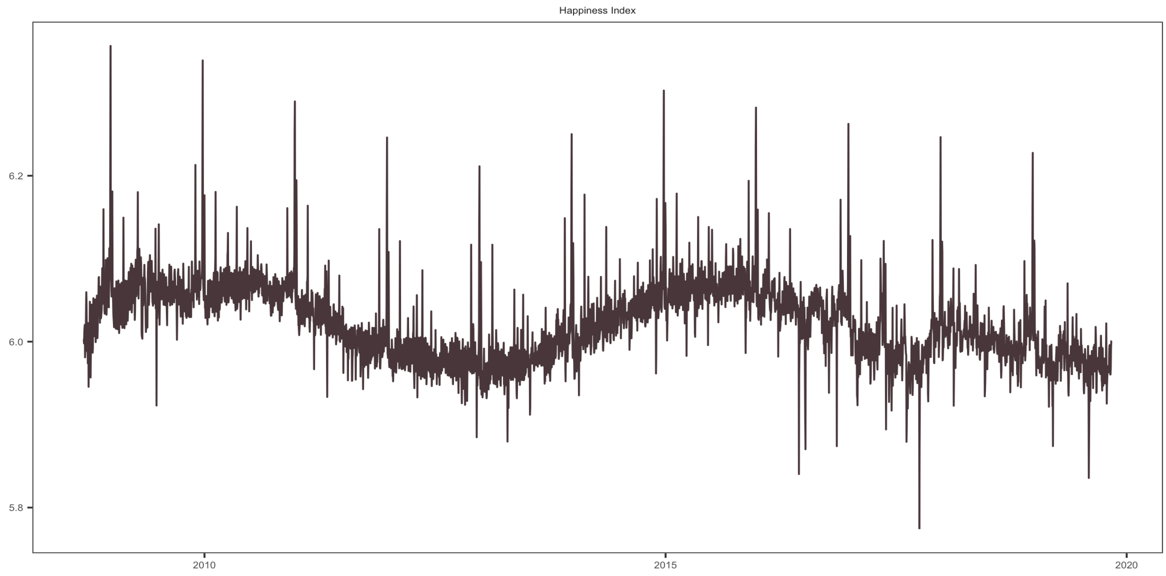


Table A.1: Descriptives statistics

| | AUD/USD | CAD/USD | USD/EUR | JPY/USD | NZD/USD | NOK/USD | SEK/USD | USD/CHF | USD/GBP |
|---|---|---|---|---|---|---|---|---|---|
| Mean | −0.001446 | −0.001513 | 0.000027 | −0.001920 | −0.003220 | 0.003419 | 0.003417 | 0.007967 | −0.005850 |
| Median | 0.000000 | 0.000000 | 0.000000 | 0.004672 | −0.014577 | 0.000000 | 0.000000 | −0.005227 | 0.000000 |
| Maximum | 7.738583 | 4.337515 | 4.617150 | 3.710207 | 6.645562 | 5.015097 | 3.541090 | 11.41652 | 4.428722 |
| Minimum | −7.155106 | −5.046215 | −3.844055 | −4.609788 | −5.877755 | −6.458059 | −5.547429 | −8.478539 | −8.287932 |
| Std. Dev. | 0.782524 | 0.600617 | 0.591686 | 0.628114 | 0.836140 | 0.766275 | 0.748936 | 0.668137 | 0.607826 |
| Skewness | 0.280852 | −0.107223 | 0.104934 | −0.257461 | 0.384603 | 0.006976 | −0.166652 | 1.012279 | −0.647510 |
| Kurtosis | 11.59204 | 7.848529 | 6.155422 | 7.451331 | 8.610568 | 7.457785 | 6.648177 | 33.96093 | 14.80975 |
| JB | 12887.76 | 4094.509 | 1738.461 | 3490.485 | 5574.861 | 3454.424 | 2332.894 | 167345.6 | 24536.12 |
| 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 | 4172 | 4172 | 4172 | 4172 | 4172 | 4172 | 4172 | 4172 | 4172 |

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 | USD/EUR | JPY/USD | NZD/USD | NOK/USD | SEK/USD | USD/CHF | USD/GBP |
|---|---|---|---|---|---|---|---|---|---|
| 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 |
| USD/EUR | -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 |
| USD/CHF | -0.15 | -0.35 | 0.75 | -0.4 | -0.4 | -0.59 | -0.61 | 1 | 0.47 |
| USD/GBP | -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