Investor Sentiment and Dollar-Pound Exchange Rate Returns: Evidence from Over a Century of Data Using a Cross-Quantilogram Approach

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Abstract

In this paper, we investigate the cross-quantile dependence between investor sentiment and exchange rate returns using an extreme quantile approach and based on daily data covering the period January 4, 1905 to January 3, 2006. As a proxy of investor sentiment, we use the bull (positive) minus bear (negative) spread of the sentiment measure constructed by Garcia (2013). We find that the lower quantiles of investor sentiment have a positive and significant effect on the quantiles of dollar-pound exchange rate returns. However, the sign of dependence is reversed for the median to higher quantiles of the distribution of the sentiment. Our finding holds even after controlling for the performance of the equity market, and provides additional evidence that investor sentiment can augment conventional predictors with respect to the future evolution of exchange rate returns.

Keywords: Exchange rate, quantile dependence, investor sentiment, behavioral finance

JEL Codes: C14, C22, F31

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1 Introduction

Both the theoretical and empirical literature in finance suggest that investor sentiment − the prevailing market consensus about future cash flows and investment risks that is normally not justified by rational rules − affect capital market prices. Theoretically, the noise trader theory (Black (1986), De Long et al. (1990)) posits that market prices can deviate from their fundamental values as a result of investor sentiment even without fundamental risk. Moreover, evidence abound in the empirical literature of how investor sentiment partly drive outcomes in capital markets such as the foreign exchange market (see e.g., Hopper (1997), Menkhoff & Rebitzky (2008), Heiden et al. (2013), Plakandaras et al. (2015), Ho et al. (2017), Singh (2019), Jaworski (2019)). For example, Hopper (1997) in his review of the literature show that exchange rates are affected by market sentiment, at least in the short run, rather than by economic fundamentals. In addition, Heiden et al. (2013), Plakandaras et al. (2015), and Jaworski (2019) provide evidence to show the predictive power of investor sentiment for a range of exchange rates.

Although studies have investigated how investor sentiment influence prices on the foreign exchange market, the concentration has rather been thin compared to studies analyzing how investor sentiment drive prices on the stock market (see e.g., Brown & Cliff (2004), Baker & Wurgler (2006, 2007), Baker et al. (2012), Huang et al. (2015), Balcilar et al. (2018), and Zhou (2018) for detailed reviews of this literature). Further, most of the existing studies on investor sentiment and exchange rate returns have focused on mean-to-mean dependence, neglecting potential tail dependence between the variables. To the extent that financial time series exhibit nonlinear dynamics (Rapach & Wohar (2006), Christopoulos & León-Ledesma (2007)) and tail dependence (Hartmann et al. (2004)), the relatioship between investor sentiment and exchange rate returns may not be linear and may vary across the joint distribution. In this context, we aim to add to this strand of literature, by studying the cross-quantile dependence of the U.S. dollar to Bristish pound exchange rates return on investor sentiment using the cross-quantilogram (CQ) method of Han et al. (2016). Beyond the global significance of the foreign exchange market in terms of scale and liquidity (Bank for International Settlements, (BIS 2019)), our study is motivated by the historical and global relevance of the two currencies in international trade. In addition, the CQ method enables us to document new insights about the direction and sign of the spillover influence from investor sentiment to exchange rate returns for varying market conditions i.e., during bear (lower quantiles), normal (median) and bull (upper quantiles) market conditions. Furthermore, we employ the partial cross-quantilogram (PCQ) model and rolling sample estimation technique to respectively, ascertain whether the dependence structure is moderated by equity market performance or shifts over time.

The rest of the paper is structured as follows. Section 2 discusses the cross-quantilogram method, followed by Section 3, which describes the data. Section 4 presents and discusses the empirical results, and Section 5 concludes.

2 Methodology

We investigate the interdependence and spillover influence between dollar-pound exchange rate returns and stock market sentiment by implementing the cross-quantilogram method of Han et al. (2016). The method is appealing in the sense that it measures the correlation and causal dependence between pairs of variables at stationary levels for different quantiles (lower, middle, and upper) of the distributions. That is, it provides a complete picture of the relationship between the variables under varying market conditions. Moreover, it does not rely on moment conditions and also makes the measurement of cross-correlation for very long lags possible.

Let $\{x_{i,t}, t \in \mathbb{Z}\}$, i = 1, 2 denote two strictly stationary series. In the context of this paper, $x_{1,t}$ and $x_{2,t}$ respectively represent dollar-pound exchange rate returns and stock market sentiment. Also, let $F_i(\cdot)$ and $f_i(\cdot)$ denote the cumulative distribution and density functions of $x_{i,t}$, and $q_i(\alpha_i) = inf\{v : F_i(v) \geq \alpha_i\}$ for $\alpha_i \in [0, 1]$ define the corresponding quantile which captures and models observations at various locations of a marginal distribution. In contrast, the expression $(q_1(\alpha_1), q_2(\alpha_2))^\tau$ denotes the two dimensional series of quantiles in which $\alpha \equiv (\alpha_1, \alpha_2)^\tau$. The CQ for the α-quantile with k lags is defined as:

$$\rho_\alpha(k) = \frac{E[\Psi_{\alpha 1}(x_{1,t} - q_1(\alpha_1))\Psi_{\alpha 2}(x_{2,t-k} - q_2(\alpha_2))]}{\sqrt{E[\Psi^2_{\alpha 1}(x_{1,t} - q_1(\alpha_1))]}\sqrt{E[\Psi^2_{\alpha 2}(x_{2,t} - q_2(\alpha_2))]}}, \tag{1}$$

for $k = 0, \pm 1, \pm 2, ...$, and where $\Psi_\alpha(\mu) \equiv 1[\mu < 0]$. The term $1[\cdot]$ represents the indicator function, while $1[\, x_{i,t} \leq q_i(\alpha_1)]$ is called the quantile hit or quantile exceedance process. The CQ in Eq. (1) captures the serial dependence between two series at different quantiles and its sample equivalent is estimated as follows:

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \Psi_{\alpha 1}(x_{1,t} - \hat{q}_1(\alpha_1))\Psi_{\alpha 2}(x_{2,t-k} - \hat{q}_2(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T} \Psi^2_{\alpha 1}(x_{1,t} - \hat{q}_1(\alpha_1))}\sqrt{\sum_{t=k+1}^{T} \Psi^2_{\alpha 2}(\, x_{2,t-k} - \hat{q}_2(\alpha_2))}}, \tag{2}$$

The $\hat{q}_i(\alpha_i)$ parameter in Eq. (2) is the unconditional sample quantile of $x_{i,t}$ as defined in Han et al. (2016). In addition, Han et al. (2016) propose a quantile version of the Ljung-Box-Pierce statistic with the null hypothesis $H_0 : \rho_\alpha(k) = 0$ for all $k \in 1, ..., p$, against the alternative hypothesis $H_1 : \rho_\alpha(k) \neq 0$ for all $k \in 1, ..., p$:

$$\hat{Q}^{(p)}_\alpha = \frac{T(T+2)\sum_{k=1}^{T} \hat{\rho}^2_\alpha(k)}{T-k}, \tag{3}$$

where $\hat{Q}^{(p)}_\alpha$ denotes the portmanteau test of directional predictability from one time series to another according to p lags and quantile pair $\alpha = (\alpha_1, \alpha_2)$. Under the null hypothesis of no directional predictability, the asymptotic distribution of CQ is not free of nuisance parameters or noise thus, Han et al. (2016) recommend the stationary bootstrap by Politis & Romano (1994) for approximating the null distribution and conducting inference. The test uses a block bootstrap procedure to account for inherent serial dependence in the data by allowing random block lengths.

Also following Han et al. (2016), we implement the Partial Cross-quantilogram (PCQ) model which is an extension of CQ to control for all intermediate events between t and $t - k$ for the two events $x_{1,t} \leq q_{1,t}(\alpha_1)$ and $x_{2,t-k} \leq q_{2,t-k}(\alpha_2)$. The PCQ allows us to introduce control variables (Dow Jones industrial average in our context) $z_t \equiv [\Psi(x_{\alpha 3}(x_{3,t}) - q_{3,t}(\alpha_3)), ..., \Psi(x_{l,t} - q_{l,t}(\alpha_l))]^\top$, where $l = 3, ..., n$. The correlation matrix along with its inverse version can be defined as:

$$R^{-1}_{\bar{\alpha}} = E[h_t(\bar{\alpha})h(\bar{\alpha})^\top]^{-1} = P_{\bar{\alpha}} \tag{4}$$

where $h_t(\bar{\alpha}) = [\Psi(x_{1,t} - q_{1,t}(\alpha_1)), ..., \Psi_{\alpha,l}(x_{l,t} - q_{l,t}(\alpha_l))]^\top$, which is the representation of quantile hit process, and $P_{\bar{\alpha}}$ can be defined as:

$$\rho_{\bar{\alpha}|z} = -\frac{p_{\bar{\alpha},12}}{\sqrt{p_{\bar{\alpha},11}p_{\bar{\alpha},22}}} \tag{5}$$

Therefore, $\rho_{\bar{\alpha}|z}$ is the cross-quantilogram dependence that is conditional on the control variable z.

3 Data

We use daily data spanning the period January 4, 1905 to January 3, 2006 with a sample size of 27,354 for dollar-pound exchange rate returns, investor sentiment, and returns on the Dow Jones Industrial Average (DJIA). The data on the exchange rate and the DJIA are sourced from the Global Financial Database. The dollar-pound exchange rate returns are computed as the natural log first difference of the U.S. dollar to British pound exchange rates ratio. As a proxy of investor sentiment, we use the bull (positive) minus bear (negative) spread of the sentiment measure constructed by Garcia (2013), which is available for download from: `http://leeds-faculty.colorado.edu/garcia/page3.html`. The author employed the positive and negative financial dictionaries of Loughran & McDonald (2011) to count the number of positive and negative words in the daily columns "Financial Markets" and "Topics in Wall Street" from the *New York Times*. The number of positive and negative words in each column were then aggregated into word counts. Our sample period is determined by the availability of the daily sentiment data (i.e. from 1905 - 2006) [1]. Nonetheless, we perform the same analysis with weekly frequency data from July 31, 1987 to May 31, 2019 to check the robustness of our results and for the reason that our second proxy for investor sentiment is only available on a weekly basis. We use the sentiment measure of the American Association of Individual Investors (AAII) that surveys its members to measure the fraction of individual investors who are bullish, bearish, and neutral on the stock market for the six months ahead. The AAII sentiment data was obtained from: `https://www.aaii.com/sentimentsurvey/sent_results`, whereas the weekly dollar-pound exchange rates and DJIA data were sourced from the Global Financial Database.

4 Empirical Results

4.1 Main Result

In figure 1 (a and b), we provide evidence of cross-quantile dependence and spillover influence from investor sentiment to dollar-pound exchange rate returns for both the bivariate (figure 1a) and multivariate (figure 1b) cases [2]. The results are displayed in the form of heatmaps with 121 (11 x 11) cells for four different lags. However, we focus our discussion on the lag 1 results. Each cell in the heatmaps correspond to the cross-quantile

[1] The measure was discontinued after 2006 for the reason that the columns no longer appeared consistently in the *New York Times* Garcia (2013).

[2] It is worth mentioning that we performed descriptive analysis of the variables, the linear Granger causality test as well as the Broock et al. (1996) BDS test of nonlinearity to justify our choice of the CQ method and emphasize its appropriateness in capturing the nonlinear dependence structure between the variables. The summary statistics revealed that all the variables are negatively skewed with kurtosis values higher than three. Barring the weekly sentiment series, the Jarque-Bera test statistic also confirmed the absence of a normal distribution for all variables. Also, the presence of nonlinear dependence between the series was confirmed by the BDS test emphasizing that the linear Granger causality test result might be misleading. Results of the summary statistics, linear Granger causality test, and the BDS test are available upon request.

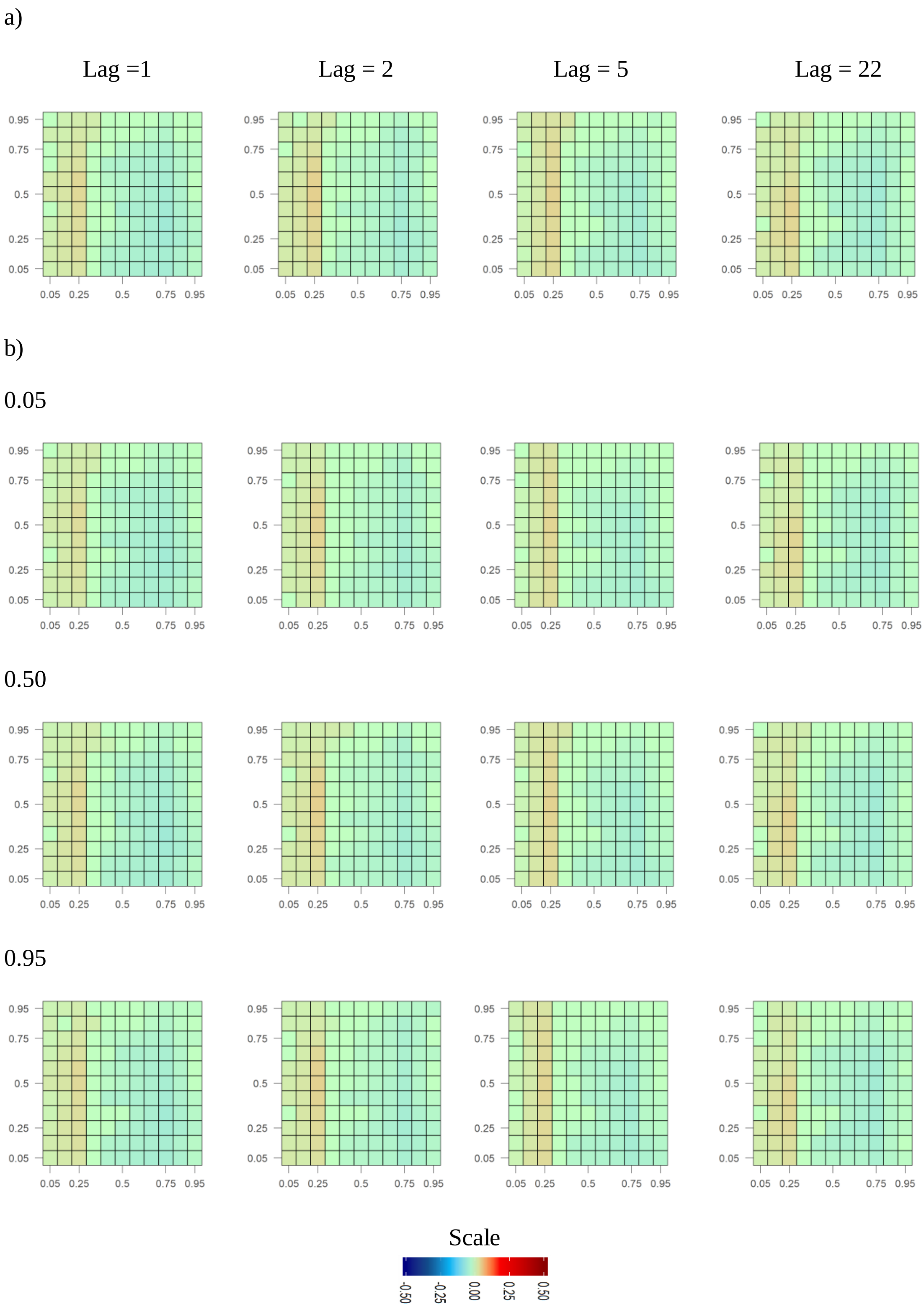

Figure 1: Heatmaps of cross-correlation between daily dollar-pound exchange rate returns and investor sentiment for bivariate (a) and multivariate (b) cases. Note: These figures show the CQ in the form of heatmaps. The quantile levels with no significant directional predictability are set to zero. The colored rectangles are the predictable regions where the Box–Ljung test statistic is statistically significant. In each heat map, the horizontal axis represents sentiment quantiles, while the vertical axis represents exchange rate return quantiles.

unconditional bivariate correlation between investor sentiment (x-axis) and dollar-pound exchange rate returns (y-axis). The strength and direction of the correlation is indicated by the color scale with statistically insignificant correlation set to zero.

Figure 1a shows that the lower quantiles of investor sentiment have positive and significant influence on the dollar-pound exchange rate returns across the different quantiles of the return distribution. That is, weak sentiment of investors increases the dollar-pound exchange rate return. This result implies that when investors are bearish they reduce their demand for assets denominated in U.S. dollars, causing the dollar to depreciate due to capital outflows, which in turn increases the return on the dollar-pound exchange rate. On the other hand, the median to higher quantiles of investor sentiment have negative and significant influence on the dollar-pound exchange rate returns across the different quantiles of the return distribution. In other words, when investors' sentiment is high and improves further, the return on the dollar-pound exchange rate decreases. This suggests that during normal and bullish conditions, investors increase their demand for dollar denominated assets causing the dollar to appreciate in value, thereby decreasing the dollar-pound exchange rate returns. Note that this result is consistent across the four different lags indicating that the dependence structure holds both in the short and longer-runs. In sum, our results not only emphasize the interdependence between the stock and currency markets but also highlights the appeal of the CQ approach in capturing cross-quantile asymmetries in the dependence structure.

Next, we ascertain the cross-quantile dependence between the dollar-pound exchange rate returns and investor sentiment after controlling for the performance of the equity market. This analysis aims to understand the nature of the dependence structure between the dollar-pound exchange rate returns and investor sentiment under different states of the equity market since it is also known to be affected by investor sentiment. We use the DJIA returns as a proxy for equity market performance, and the partial cross-quantilogram method described in section 2. The analysis is under taken for three different market conditions - extreme downside (0.05), normal (0.50), and extreme upside (0.95). Figure 1b shows that even after controlling for equity market performance, the results are consistent with the findings of the preceding paragraph. We observe a significant positive dependence across the quantiles of the distribution of the dollar-pound exchange rate returns in relation with the lower quantiles of the distribution of the sentiment. However, the sign of the dependence is reversed for the median to higher quantiles of the distribution of the sentiment. Again, this result is found to hold for the four different lags .

Further to the above, given that adding stock returns does not change the conclusions of the bivariate analysis, we examine the time-varying nature of the interdependence between dollar-pound exchange rate returns and investor sentiment using a rolling sampling method with a window of five years in the bivariate context of exchange rate returns and sentiment. The motivation is to capture any potential shift, say due to structural breaks, in the dependence structure over time across quantiles. The analysis is done for the initial window, then subsequently shifting it by one day till the end of the sample. The results are reported in Figure 2 where the horizontal axis indicates the starting year of the rolling window and the vertical axis represents the quantile hits for the dollar-pound exchange rate returns. The results indeed reveal that the co-dependence of exchange rate returns with investor sentiment is dynamic with the magnitude of the dependence varying over time. In particular, we find that, the depreciation of the dollar pound exchange rate which is observed at lower quantiles of the investor sentiment for the entire conditional

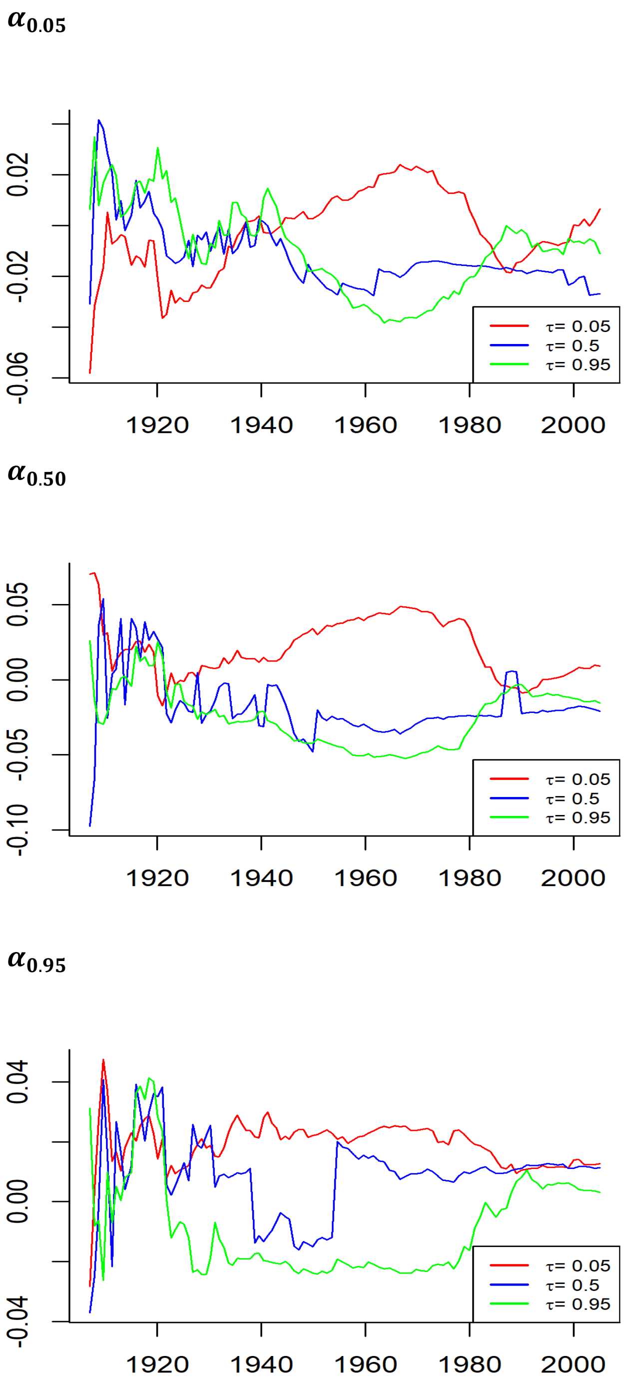

Figure 2: Rolling CQ between daily dollar-pound exchange rate returns and investor sentiment. Note: The vertical (horizontal) axis represents the quantile hits for the dollar-pound exchange rate returns (time). The starting year of the rolling window is marked on the horizontal axis. The alpha indicates 5%, 50%, and 95% quantiles for the investor sentiment while, the red, blue, and green lines represent the 5%, 50%, and 95% quantiles for the dollar-pound exchange rate returns. Lag p=1.

distribution of exchange rate returns generally holds for the entire sample period barring the initial few years. Similarly, the appreciation of the dollar relative to the pound for sentiments around the median and above, for the entire conditional distribution of exchange rate returns can be observed for the entire sample period barring the initial years of the rolling approach. These initial years correspond to period before the commencement of World War I, and does involve a lot of zeros in the exchange rate returns, and hence, cannot be completely relied upon for proper statistical inference.

4.2 Robustness Check

In this subsection, we examine the robustness of the earlier findings by performing the same analysis with weekly frequency data that is available till recent dates of 31st May, 2019, as mentioned in section 3. The results are displayed in Figures 3 and 4 for both the full and rolling sample cases. In general, the full sample results (i.e. Figure 3) show evidence of strong positive influence from investor sentiment to the dollar-pound exchange rate returns across the quantiles of the joint distribution, however, the relationship dies out nearly completely as we move to lags beyond 1 (which corresponds to basically 5 days in terms of the daily data). That is to say, in general, investor sentiment movements, barring at the immediate horizon, cause an appreciation of the U.S. dollar relative to the British pound, thereby decreasing the returns on the dollar-pound exchange rate. This result compared to the finding presented earlier (Section 4.1) might be due to the rise in significance of the U.S. dollar in international trade after World War II and primarily after the breakdown of the Bretton Woods system (Eichengreen & Flandreau (2009)), such that investors want to hold the dollar as a safe-haven asset during periods of pessimism. In addition, the rolling sample result (i.e. Figure 4) confirms that, in essence the above story holds over the entire sample period.[3]

5 Conclusion

This paper contributes to the ongoing literature on the interdependence between investor sentiment and exchange rate returns. Unlike, the existing literature that focuses on mean-to-mean dependence, we use the cross-quantilogram approach that has the potential to detect cross-quantile asymmetries in the dependence structure and also provide information on the direction and sign of the spillover effect. Moreover, we employ the partial cross-quantilogram model and rolling sample estimation technique to respectively, examine if the dependence structure is moderated by equity market performance or shifts

[3]Recently, Pastor & Veronesi (2019), point out that Democratic governments in the US are nominated when agents are risk-averse, i.e., bearish. Given this, as an additional analysis, we estimate exponential generalized autoregressive conditional heteroskedasticity (EGARCH) models for dollar-pound exchange rate returns using a dummy variable which takes a value of 1 under the Democratic regime and 0 otherwise (with the information derived from: `https://www.enchantedlearning.com/history/us/pres/list.shtml`), as a measure of sentiment. In particular, we look at both monthly data over the period of 1791:02 to 2019:05, and daily data covering January 3, 1900 to May 31, 2019, and find that Democratic regimes indeed do cause a depreciation of the dollar relative to the pound and also increases its volatility (possibly, since dollar-denominated assets are perceived to be risky) at the highest level of statistical significance. In addition, a rolling window estimation, suggested that the Democratic dummy started to appreciate the dollar in a statistically significant manner primarily after World War II, again suggesting dollar's transformation to a safe-haven status. Complete details of these results are available upon request from the authors.

Figure 3: Heatmaps of cross-correlation between weekly dollar-pound exchange rate returns and investor sentiment for bivariate (a) and multivariate (b) cases. Note: These figures show the CQ in the form of heatmaps. The quantile levels with no significant directional predictability are set to zero. The colored rectangles are the predictable regions where the Box–Ljung test statistic is statistically significant. In each heat map, the horizontal axis represents sentiment quantiles, while the vertical axis represents exchange rate return quantiles.

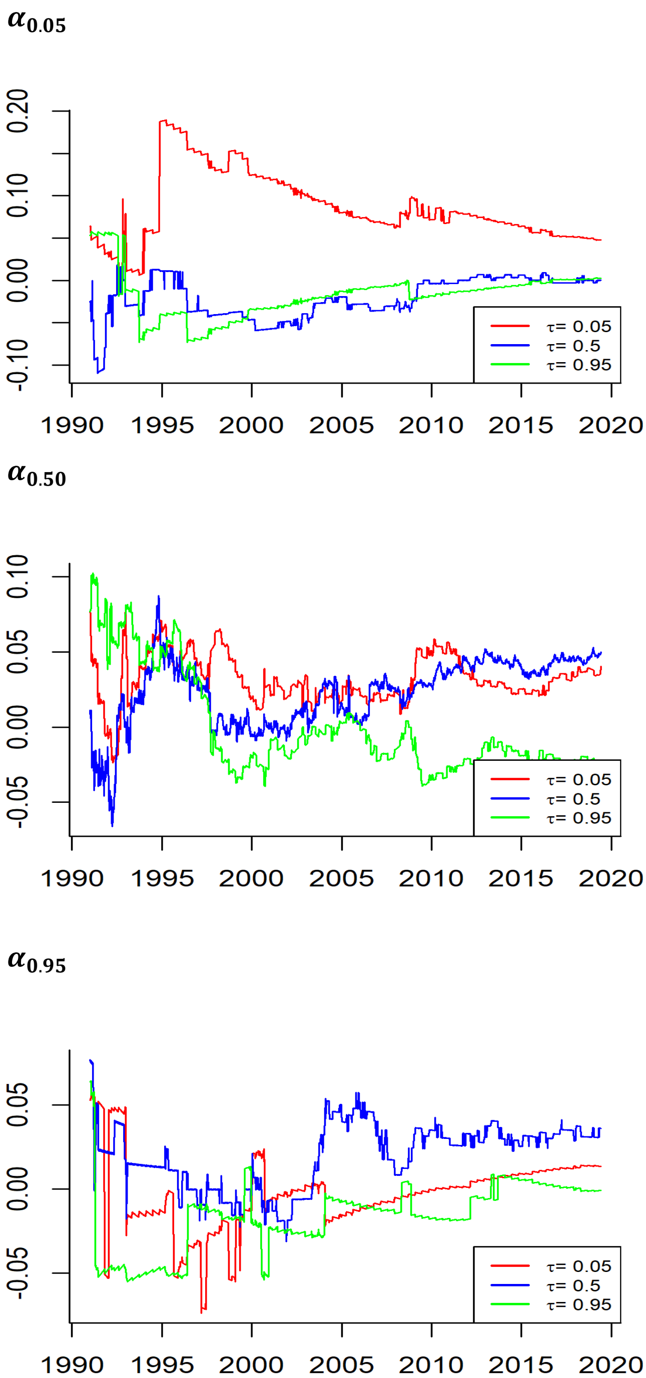

Figure 4: Rolling CQ between weekly dollar-pound exchange rate returns and investor sentiment. Note: The vertical (horizontal) axis represents the quantile hits for the dollar-pound exchange rate returns (time). The starting year of the rolling window is marked on the horizontal axis. The alpha indicates 5%, 50%, and 95% quantiles for the investor sentiment while, the red, blue, and green lines represent the 5%, 50%, and 95% quantiles for the dollar-pound exchange rate returns. Lag p=1.

over time. Our analysis is based on daily data covering the period 4 January, 1905 to 3 January, 2006.

Results of our analysis indicate that during bearish sentiments, investors decrease their demand for U.S. dollar denominated assets thereby causing the dollar to depreciate relative to the British pound. In contrast, during normal and bullish market conditions when investors' sentiment are high, the demand for dollar denominated assets increases causing the dollar to appreciate relative to the pound. Our finding is robust even after controlling for equity market performance and using an alternative updated measure of investor sentiment (primarily in the short-run). But it seems that in recent years with the dollar acting as a safe haven, movements in investor sentiment, irrespective of its initial state, always causes the dollar to appreciate.

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