Information Processing of Foreign Exchange News: Extending the Overshooting Model to Include Qualitative Information from News Sentiment

Complete Research

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Abstract

In a globalized world, the volume of international trade is based on both import and export prices, thereby making a country's economy highly dependent on exchange rates. In order to study exchange rate movements, one frequently exploits the so-called Dornbusch overshooting model. However, the model is controversial from a theoretical point of view: it presupposes the processing of information, though this is not directly reflected by the underlying variables. As a remedy, this paper investigates a potential cognitive bias by including textual news content, thus adjusting for information dissemination. As such, we perform a multivariate analysis to compare the classical overshooting model with an extended variant that includes news sentiment. Our results show that news has a substantial explanatory power of 11 % of the exchange rate forecasting error variance. In addition, we also find statistical evidence that a shock in news sentiment may lead to overshooting.

Keywords: Information processing, economics of IS, decision analysis, country-level analysis, behavioral science, econometric analyses, cognitive bias, text mining

Introduction

Global trade relies not only upon global capital flows but also on a liquid trading mechanism to exchange currencies. The exchange rate gives the price at which one unit of one currency exchanges for one unit of another. Exchange rates are seldom fixed, instead policy makers may be tempted to use monetary policy to influence the domestic exchange rate. A weak domestic currency may result in a competitive advantage for an export-driven country and, accordingly, foreign investment in the domestic country may rise as investment opportunities for foreign investors become cheaper. In addition, several other influences affect exchange rates, frequently resulting into a highly volatile pattern. For instance, Figure 1 visualizes the monthly exchange rate between British pound (GBP) and U. S. dollar (USD) where we observe a fluctuations of different magnitude.

Since global trade and capital flows significantly depend on exchange rates (Bailey & Millard 2001; Bernard & Jensen 2004), it is of great interest for economists to understand the long-term movements and short-term fluctuations of exchange rates.

Figure 1. Monthly Exchange Rate between British Pound and U. S. Dollar from July 15, 2003 until May 15, 2012
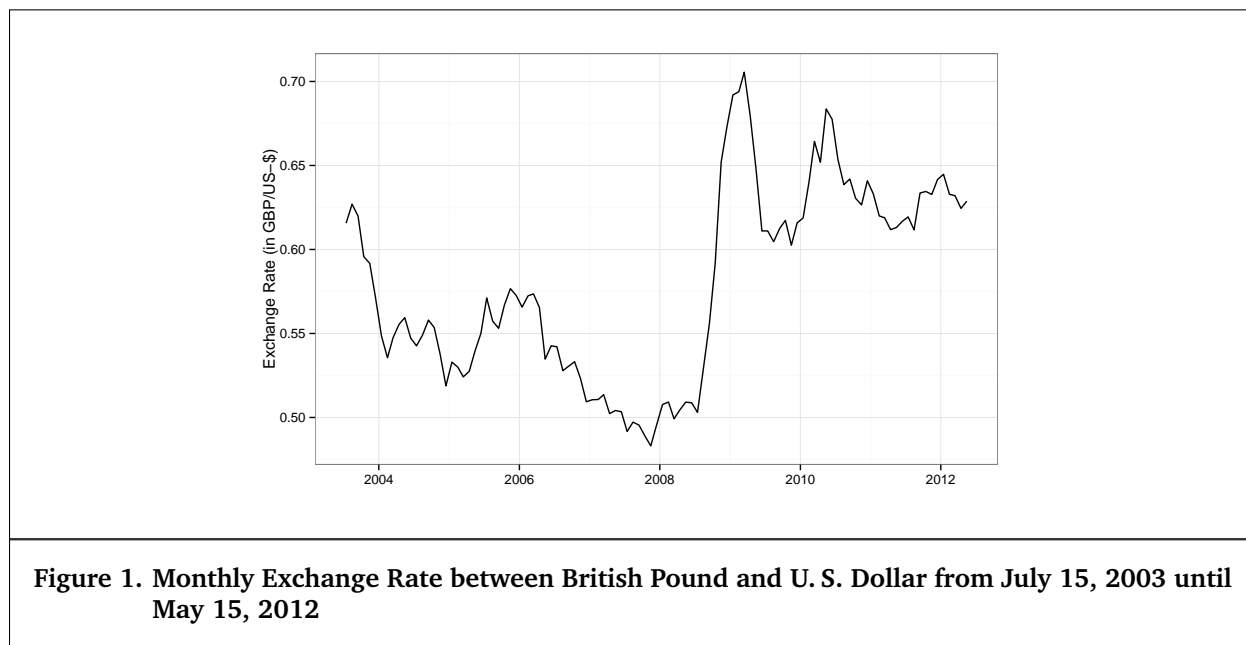
The so-called Dornbusch model is a vehicle to explain exchange rate movements according to monetary policy. In fact, it is one of the most frequently cited papers in exchange rate theory, since *"the Dornbusch model defines a high-water mark of theoretical simplicity and elegance in international finance"*. As Nobel laureate Rogoff (2002) further notes in an overview paper, the overshooting model *"still stands today as fundamental; even today, the model in its original form remains relevant for policy analysis"*. The model itself is based on the following assumptions to model the long-run and short-run changes in exchange rates. First of all, the model assumes the law of one price, since otherwise arbitrageurs would buy goods in the underpriced country and sell it in the overpriced one. However, in order to exploit such an arbitrage, one must transport goods between the two countries and it thus requires time until the law of one price is restored. Accordingly, the exchange rate in the long-run then reflects price inflation rate differentials between two countries. In contrast, the exchange rate in the short-run reflects the interest rate differentials between two countries. The justification is that markets can adapt quickly to interest rate differentials since capital is highly mobile.

The overshooting model also contributes to the theory of *information processing*: Market participants process information that result into movements of exchange rates. When these movements are triggered by monetary shocks, the price adjustments can even evoke a short-run *overshooting*. The overshooting describes a situation where a short-run depreciation of the exchange rate exceeds the depreciation of the long-run equilibrium. Its existence has been empirically verified in several publications (e. g. Bjørnland 2009; Sims 1992). Other papers sometimes find a delayed overshooting (e. g. Eichenbaum & Evans 1995; Faust & Rogers 2003; Heinlein & Krolzig 2012) or even no evidence of overshooting (e. g. Backus 1984). In order to shed light into the overshooting puzzle, this paper extends the classical overshooting model as follows. We include an additional variable representing the qualitative information processed by investors, which we extract from the textual content of economic news. We can then investigate the question whether also quantitative information can evoke an overshooting of exchange rates.

Information Systems research, and information processing theory in particular, can provide a behavioral explanation for deviations from economic models. For example, qualitative information can induce an overshooting through a *cognitive bias*. In order to investigate such a cognitive bias, we incorporate a

comprehensive analysis of news sentiment into the overshooting model. We thus study the impact of economic news on exchange rates by performing a so-called *sentiment analysis*. A sentiment analysis is as common methodology from Information Systems research to measure the positivity and negativity of the written content. Sentiment analysis is, in fact, frequently exploited to extract subjective information from text sources, as well as to measure how market participants perceive and react to news. In our subsequent evaluation, we choose economic news covering the exchange rate of two countries, namely, Great Britain and the United States of America. Altogether, we can formulate our hypotheses as follows:

Hypothesis A: Qualitative information as measured by news sentiment affects exchange rate significantly.

Hypothesis B: Consistent with economic theory, a shock in news sentiment does not result into an overshooting of exchange rates.

Interestingly, we will later reject Hypothesis B and, contrarily, show that exchange rates indeed overshoot after a shock in news sentiment. We regard this effect as a cognitive bias induced by qualitative information that investors treat differently over time (c.f. Hirshleifer et al. 2011). To investigate this cognitive bias, we implement a vector error correction model (VECM). The VECM enables us to empirically study effects of monetary shocks on the exchange rate. In addition, VECM models and similar vector autoregession models (VAR) have gained traction recently (e.g. Bernanke et al. 2004; Jang & Ogaki 2004), since these models entail several advantages. For instance, one does not need to identify the correct model specification other than in many microeconomic models as relations are extracted directly from the data (Lütkepohl 2007). In order to investigate the above hypotheses, we follow a two-step procedure: first, we estimate the classical overshooting model. Second, we extend the model by including a variable for news sentiment from the Thomson Reuters News Archive. Our findings then reveal a significant impact of news sentiment on the GBP/USD exchange rate, accounting for up to $10.97\,\%$ of the forecasting error variance. We thus find evidence that qualitative information in economic news have an explanatory power for the movement of the exchange rate.

The remainder of this paper is structured as follows. Section 2 provides an overview of previous research related to the information processing around exchange rates. Section 3 then introduces the classical over-shooting model by Dornbusch, as well as our extended model including news sentiment. This model is then evaluated in Section 4 by measuring the influence of news sentiment on exchange rates. Finally, we consolidate our main findings and provide an outlook for further research in Section 5.

Related Work

This section first provides an overview on the information processing of financial news. We then present related works that link sentiment analysis to econometric theory, as well as previous contributions to the classical overshooting model. In addition, we investigate literature at the interaction between financial news and exchange rates. This section concludes with our research framework, in which we motivate a combination of the classical overshooting model with qualitative information to study the fluctuation of exchange rates.

Information Processing of Financial News

Recent technological advancements enable investors to acquire inexpensive and quick access to information. When novel information is released to the market, it reaches – potentially – a wide range of investors and triggers a corresponding price reaction. Assuming the so-called semi-strong form of market efficiency (Fama 1970; Fama 1965), this asset price reaction will occur shortly after a news disclosure. Financial news disclosures are an important source of information for investors when deciding upon an investment. How markets react to news announcements has been the focus of many research publications (e.g. Cenesizoglu

2015; Cutler et al. 1989; Pearce & Roley, V. Vance 1985; Shiller 2005). All the aforementioned papers have found a discernible relationship between news releases and stock returns.

Investors may interpret news differently depending on prior beliefs and their information processing skills (Alfano et al. 2015a, 2015b). In fact, the subjective interpretation of the same information varies significantly across different audiences (Liebmann et al. 2012). A possible reason lies in the cognitive biases of investors, such as overconfidence, overreaction, representative bias, information bias and various other predictable human errors in reasoning and information processing (Friesen & Weller 2006). It is thus at the heart of Information Systems research to study how decision makers process and act upon information.

Most of the information in financial news is of a qualitative nature, containing essential facts that are difficult to decode. Furthermore, information in the form of textual news also provides valuable insights (Henry 2008; Henry & Leone 2009; Loughran & McDonald 2011; Siering 2013; Tetlock 2007). Hence, information processing has been the subject of many Information Systems research publications. For example, Siering (2013) examined the relationship between media sentiment and investor attention, finding that the positive impact of media sentiment on returns is increased when investor attention is high. On top of that, news sentiment can be utilized to analyze how information is processed since investors and analysts perceive novel information differently. Liebmann et al. (2012) comes to the conclusion that investors rapidly translate novel information into transactions whereas analysts wait to respond. Thus, these research questions are placed at the intersection between Information Systems research, behavioral finance and economics.

Sentiment Analysis in Information Systems Research

Methods that extract the tone of textual documents are referred to as opinion mining or *sentiment analysis*. Sentiment analysis can be utilized to extract subjective information from text sources, as well as to measure how market participants perceive and react upon financial materials. Here, one uses the observed price reactions following a financial disclosure to validate the performance of a routine for sentiment analysis. Sentiment analysis of news sheds lights into the effect of news tone on financial markets. Previous research has focused on how human agents process the sentiment of financial news. For instance, empirical evidence highlights a noticeable relationship between new information and stock market movements (e. g. Antweiler & Frank 2004; Feuerriegel et al. 2015, 2016; Groth & Muntermann 2011; Muntermann & Guettler 2007; Tetlock 2007).

Information Systems research has developed various approaches to measure sentiment, since sentiment analysis is deployed across various domains and for different textual sources. For instance, Pang and Lee (2008) provide a comprehensive domain-independent survey. Within the finance domain, recent literature reviews (Minev et al. 2012; Mittermayer & Knolmayer 2006b; Nassirtoussi et al. 2014) focus on studies aimed at stock market prediction. Financial text mining research predominantly deploys *dictionary-based methods* (cp. Demers & Vega 2010; Henry 2008; Jegadeesh & Wu 2013; Loughran & McDonald 2011; Tetlock et al. 2008). Dictionary-based approaches produce reliable results by counting the frequency of pre-defined negative and positive words from a given dictionary. *Machine learning methods* (e. g. Antweiler & Frank 2004; Fehrer & Feuerriegel 2015; Li 2010; Mittermayer & Knolmayer 2006a; Schumaker & Chen 2009) represent a variety of methods, but may be subject to overfitting (Sharma & Dey 2012). A remedy may be found in regularization methods that utilize variable selection to generate domain-dependent dictionaries (Pröllochs et al. 2015b, 2015c). Since this paper addresses the application of sentiment analysis only in the domain of foreign exchange rates, we utilize a dictionary-based approach. This allows for easier verification of our results. Furthermore, dictionary approaches seem to be the technique of choice nowadays in finance literature.

Overshooting Model

After the end of the Bretton Woods era of fixed exchange rates, considerable effort has been invested to understand the fluctuation of floating exchange rates. One of the first floating exchange rate models has been the monetary approach model, which is based on the demand and supply of money. Among one of several approaches that extend the monetary approach is the Dornbusch Overshooting model developed in 1976. It represents not only a well-known model in exchange rate theory but has been extensively studied ever since (Rogoff 2002).

A broad range of research has concentrated on the assumptions of the model (e. g. Frankel 1979). Some studies have been unable to find evidence of an overshooting of the real exchange rate to a monetary shock (e. g. Backus 1984); others have found a delayed response of up to three years rather than a theoretical contemporaneous response (e. g. Eichenbaum & Evans 1995; Faust & Rogers 2003; Heinlein & Krolzig 2012); while several studies have empirically supported the hypothesis of overshooting (e. g. Bjørnland 2009; Sims 1992). These differences in outcomes may arise from different realizations of the underlying assumptions, while many attribute these results to unmeasured effects that drive exchange rates, such as news disclosures.

Exchange rates can be significantly influenced by upcoming news, since exchange rates must incorporate expectations of future expectations. Accordingly, several studies (e. g. Edwards 1983; Frenkel 1981; Hoffman & Schlagenhauf 1985) consider news in their evaluations. These mostly account for news by theoretical assumptions regarding the monetary model. For example, Frenkel (1981) represents news as the difference between the interest differential and the expected interest differential.[1] Furthermore, Edwards (1983), as well as Dornbusch et al. (1980), support a news component which suggests that upcoming news explains market forecasting error. In contrast, Eichenbaum and Evans (1995) note that news has a delayed effect on the exchange rate. At this point, it is worth mentioning that aforementioned research papers only consider events of news releases and neglect the actual qualitative content.

News and Exchange Rates

In addition to the above overshooting model, several studies have analyzed the behavior of exchange rates on a daily basis by considering upcoming macroeconomic news. Instead of macroeconomic approaches (such as the monetary or portfolio balance approach), these papers include an additional variable to measure the impact of news. For example, Galati and Ho (2003) introduce a variable that estimates the deviation from the expected macroeconomic announcement and the real announcement. The authors conclude that macroeconomic news influences daily movements of the euro/dollar exchange rate. Ehrmann and Fratzscher (2005) also find evidence that news affects daily movements of the exchange rate by using a similar news variable.

Furthermore, Zhang et al. (2005) analyze the impact of news on exchange rates by evaluating news articles and economic data using regression techniques that reflect the monetary model of Dornbusch and Frankel. The authors include a news index in the regression determining the number of *good* and *bad* news releases. Eddelbüttel and McCurdy (1998), as well as Peramunetilleke and Wong (2002), conduct an analysis of news headlines using natural language processing in order to classify their polarity. Eddelbüttel and McCurdy (1998) find empirical evidence for relationship between the volatility of exchange rates and the frequency of news. Conversely, Peramunetilleke and Wong (2002) focus on the ability of news to forecast exchange rates. In summary, prior research has concentrated on count measures that incorporate news. In comparison, we analyze qualitative content and run an extensive sentiment analysis, which allows us to determine the tone of news.

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1 The argument is that upcoming news between the price setting of the forward rate in $t-1$ and the spot rate in t explains the market forecasting error.

Research Framework

All in all, this motivates our research question (see Figure 2) of how news affects exchange rates. A wide variety of previous research explains exchange rate behavior with reference to monetary shocks, but also identifies a lack of information that may explain controversial outcomes. We are aware of only a few references from information processing theory which incorporate a news variable into the macroeconomic analysis. To our knowledge, most research papers only count the number of *good* or *bad* news announcements (e. g. Zhang et al. 2005) or investigate the difference between the expected and real outcomes of macroeconomic data (e. g. Galati & Ho 2003). In contrast, we analyze the qualitative content and perform a comprehensive sentiment analysis that extracts the news tone. Subsequently, we extend the Dornbusch overshooting model by our news sentiment variable. Combining recent advances in text mining with the traditional Dornbusch overshooting model makes it possible to fill the above research gap and to explain overshooting as a cognitive bias of investors.
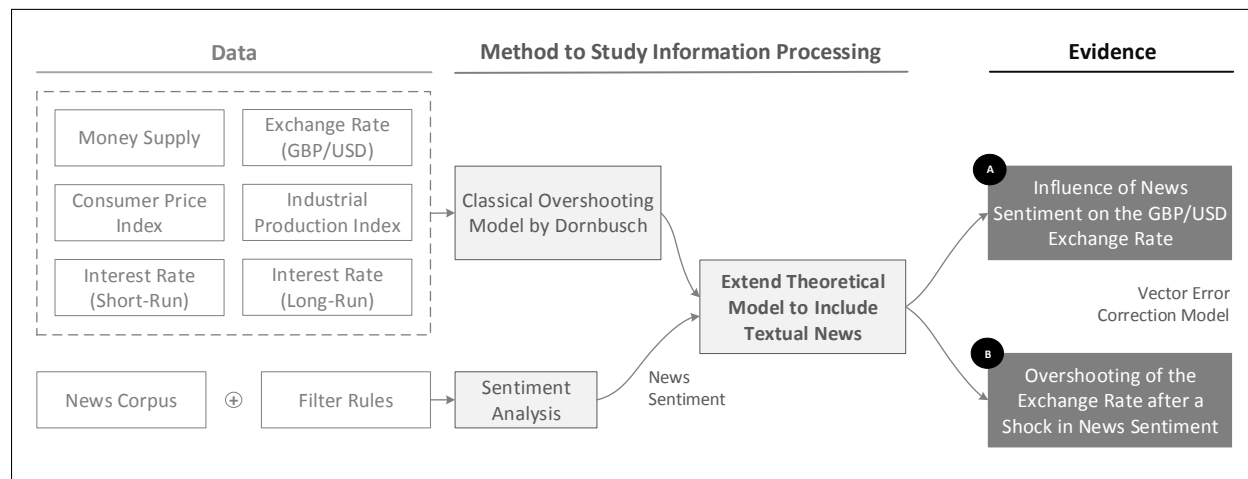
Figure 2. Research Framework Shows How to Study the Information Processing of Foreign Exchange News by Extending the Overshooting Model to Include Qualitative Information from News Sentiment

Model Specification

This section introduces the overshooting model, which enables us to study how different shocks (such as monetary or news shocks) affect the exchange rate. We first describe the overshooting model briefly and then outline empirical implementation. Finally, we show how to measure news sentiment and how we integrate it into the overshooting model.

Background: Classical Overshooting Model by Dornbusch

Let us consider two different countries with two different currencies. While these countries have traded their currencies at a fixed exchange rate in the Bretton Woods era, these are no longer fixed but floating and can be traded in the market. One of the first models to describe floating exchange rates is given by the Dornbusch overshooting model (Dornbusch 1976). Its idea is to combine sticky prices in the short-run and the instantaneous adjustment of capital markets. Capital markets react with perfect foresight, which yields a rational, anticipated depreciation. However, the exchange rate may overshoot in the short-run.

Dornbusch's model assumes that the home country is small, which implies that the exchange rate is exogenously determined. Furthermore, the model is based on three further key assumptions, namely, uncovered interest rate parity, rational expectations, and price stickiness in the short-run. The latter, price stickiness, implies that money supply has liquidity effects. As a result, a one-time, permanent increase in the money supply m causes a fall in the domestic interest rate i. Under high capital mobility, this may result in capital outflows and the exchange rate e thus depreciates.[2] We then ensure the interest rate parity condition

$$i = i^* + \theta(e - \bar{e}), \tag{1}$$

which sets the domestic interest rate i equal to the foreign interest rate i^* plus the adjustment time θ multiplied by the difference between the exchange rate e and its (known) long-run value $\bar{e}$. Rational expectations imply that the exchange rate is expected to approach its long-run value $\bar{e}$. Hence, an expected appreciation of the domestic currency arises only when the exchange rate is above its long-run equilibrium. Thus, the exchange rate depreciates up to the currency appreciation compensating for the interest differential. In short, an increase in the money supply results in a short-run depreciation of the exchange rate. This short-run depreciation exceeds the deprecation of the long-run value of the exchange rate. This effect is what we call overshooting, i. e. the exchange rate *overshoots* its long-run depreciation (Dornbusch 1976).

We briefly present the key equations of the model in the following. As a classical building block of econometric models, we specify the money supply and the demand function for goods via

$$m - p = \phi y - \lambda i = \phi y - \lambda \left[i^* + \theta(e - \bar{e}) \right] \qquad \text{(the demand for } money\text{)}, \tag{2}$$
$$\ln D = u + \delta(e - p) + \gamma y - \sigma i \qquad \text{(the demand for } goods\text{)}, \tag{3}$$

where m is the money supply, p is the price level, y refers to the output with parameters ϕ, λ, δ, γ, σ and u. We then consider the long-run relationships of the price level $\bar{p}$ and the exchange rate $\bar{e}$ by

$$p_t = \bar{p} + (p_0 - \bar{p}) \exp(-vt), \tag{4}$$
$$e_t = \bar{e} + (e_0 - \bar{e}) \exp(-vt). \tag{5}$$

With the exchange rate throughout time in Equation (5), one can formally derive the overshooting by taking the derivative of $e(t)$ with respect to m, i. e.

$$\frac{\mathrm{d}e}{\mathrm{d}m} = 1 + \frac{1}{\lambda\theta}. \tag{6}$$

Altogether, the above derivation shows that the exchange rate will overshoot in the short-run.

VECM for Empirical Investigation of Overshooting

This section presents the methodology in order to evaluate the effects of shocks in the classical overshooting model. We thus introduce a *vector autoregressive* (VAR) model to capture the linear interdependencies among multiple time series. A VAR model describes the evolution of K endogenous variables $y_t \in \mathbb{R}^K$ over a sample period as a linear function of only their past values. Let VAR(p) denote a VAR process with p lags given by

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \tag{7}$$

with $A_i \in \mathbb{R}^{K \times K}$ and error terms $u_t \in \mathbb{R}^K$, $u_t \sim (0, \sigma_u)$ (Lütkepohl 2007; Lütkepohl & Krätzig 2004). Most time series in our dataset are integrated of order one, i. e. $I(1)$, with cointegration also being present. As a

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2   Note that the exchange rate is the ratio between the domestic currency price and foreign currency. Therefore, if a domestic currency appreciates relative to foreign currency the exchange rate depreciates.

remedy, it necessary to estimate a *vector error correction model* (VECM). The VECM can be derived from the VAR model by simple subtracting y_{t-1} from y_t. Hence, the VECM($p-1$) is given by

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + u_t, \tag{8}$$

where $\Pi = \alpha \beta^T$ specifies the cointegration relations as part of a cointegration matrix β. The variable $\Gamma_i = -(A_{i+1} + \ldots A_p)$ for $i = 1, \ldots, p-1$ is the long-run component and u_t represents the error term.

From the above Dornbusch model, we formulate the exchange rate e_t as a function

$$e_t = f(y_t, p_t, m_t, i_t) \tag{9}$$

with output y_t, price p_t, money supply m_t and an interest rate i_t at time step t. We follow standard literature (e. g. Eichenbaum & Evans 1995) to determine the effects of macroeconomic developments on the exchange rate by using a recursive ordering. As Sims (1980) noticed, there does not exist a *"unique and best way"* for the recursive ordering. Accordingly, we decide to use an approach similar to Sichei et al. (2005) and additionally include the long-run interest rate r_t in order to capture the full spread of interest rates. Hence, we obtain the recursive ordering

$$z_t = (y_t, p_t, m_t, i_t, r_t, e_t)^T . \tag{10}$$

Macroeconomic data of both countries influences the exchange rate and should thus enter the model, while the dimension of the model increases considerably. In order to reduce the number of dimensions, we create differences between the domestic and the foreign variables. For example, we obtain $y = y_t - y_t^*$ with foreign variables labeled by a star *. This implies that a shock in the home country has the same effect as in the foreign country, which is appropriate regarding the number of observations (Heinlein & Krolzig 2012).

We can identify the dynamics of shocks (Faust & Rogers 2003) by applying the Cholesky decomposition

$$\begin{pmatrix} y_t \\ p_t \\ m_t \\ i_t \\ r_t \\ e_t \end{pmatrix} = B(L) \begin{pmatrix} c_{11} & 0 & 0 & 0 & 0 & 0 \\ c_{21} & c_{22} & 0 & 0 & 0 & 0 \\ c_{31} & c_{32} & c_{33} & 0 & 0 & 0 \\ c_{41} & c_{42} & c_{43} & c_{44} & 0 & 0 \\ c_{51} & c_{52} & c_{53} & c_{54} & c_{55} & 0 \\ c_{61} & c_{62} & c_{63} & c_{64} & c_{65} & c_{66} \end{pmatrix} \begin{pmatrix} \varepsilon_t^y \\ \varepsilon_t^p \\ \varepsilon_t^m \\ \varepsilon_t^i \\ \varepsilon_t^r \\ \varepsilon_t^e \end{pmatrix} \quad \text{at time step } t, \tag{11}$$

where $B(L)$ is the lag operator, $c_{ij} \in \mathbb{R}$ the lower triangular Cholesky factor, $\varepsilon_t \in \mathbb{R}^6$ the vector of uncorrelated structural shocks, including the monetary shock ε_t^m and the exchange rate shock ε_t^e. The other four shocks refer to output, price, short-run and long-run interest rates. As a consequence of the ordering, a monetary shock has no contemporaneous impact on output and prices and still affects both the short-run and long-run interest rates, as well as the exchange rate. Therefore, the exchange rate is affected by all other variables within the econometric setup.

News Sentiment Analysis

Methods that use the textual representation of documents to measure the positivity and negativity of the content are referred to as opinion mining or *sentiment analysis*. Sentiment analysis can be utilized to extract subjective information from text sources, as well as to measure how market participants perceive and react to news.

Before we perform the sentiment analysis, we carry out several operations during a preprocessing phase. The individual steps are as follows (Manning & Schütze 1999):

1. **Tokenization.** Corpus entries are split into single words named *tokens*.

2. **Negations.** We account for the fact that negations invert the meaning of both words and sentences (Dadvar et al. 2011; Pröllochs et al. 2015a, 2016). When encountering the word *no*, each of the subsequent three words is counted as a word from the opposite dictionary. When encountering other negating terms (*rather, hardly, couldn't, wasn't, didn't, wouldn't, shouldn't, weren't, don't, doesn't, haven't, hasn't, won't, hadn't, never*), the meaning of all succeeding words is inverted.

3. **Stop word removal.** Words without deeper meaning, e. g. articles, are removed (Lewis et al. 2004).

4. **Stemming.** During the stemming process (Manning & Schütze 1999), we reduce the inflected words to their stem. In our research, we use the so-called Porter stemming algorithm.

Having completed the preprocessing phase, one can continue to analyze news sentiment. As shown in a recent study (Feuerriegel & Neumann 2013) on the robustness of sentiment analysis, the correlation between news sentiment and abnormal returns in oil markets varies across different sentiment metrics. A sentiment approach that results in a reliable correlation is the Net-Optimism metric (Demers & Vega 2010), utilizing Henry's Finance-Specific Dictionary (Henry 2008). The Net-Optimism metric s_t is applied to all news originating from a full day t. It is calculated as the difference between the number of positive $W_{\mathrm{pos}}(A)$ and negative $W_{\mathrm{neg}}(A)$ words divided by the total number of words $W_{\mathrm{tot}}(A)$ in each announcement A. Thus, Net-Optimism is defined by

$$s_t = \frac{\sum_A W_{\mathrm{pos}}(A) - W_{\mathrm{neg}}(A)}{\sum_A W_{\mathrm{tot}}(A)} \in [-1, +1]. \tag{12}$$

Extended Overshooting Model Including News Sentiment

Subsequent to the sentiment analysis, we integrate the news sentiment s_t into the classical overshooting model. We update the ordering of this extended model to

industrial production $y \to$ consumer price index $p \to$ money supply $m \to$ short-run interest rate i

$\to$ long-run interest rate $r \to$ news sentiment $s \to$ exchange rate e.

Then, we yield the following Cholesky decomposition

$$\begin{pmatrix} y_t \\ p_t \\ m_t \\ i_t \\ r_t \\ s_t \\ e_t \end{pmatrix} = B(L) \begin{pmatrix} c_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ c_{21} & c_{22} & 0 & 0 & 0 & 0 & 0 \\ c_{31} & c_{32} & c_{33} & 0 & 0 & 0 & 0 \\ c_{41} & c_{42} & c_{43} & c_{44} & 0 & 0 & 0 \\ c_{51} & c_{52} & c_{53} & c_{54} & c_{55} & 0 & 0 \\ c_{61} & c_{62} & c_{63} & c_{64} & c_{65} & c_{66} & 0 \\ c_{71} & c_{72} & c_{73} & c_{74} & c_{75} & c_{76} & c_{77} \end{pmatrix} \begin{pmatrix} \varepsilon_t^y \\ \varepsilon_t^p \\ \varepsilon_t^m \\ \varepsilon_t^i \\ \varepsilon_t^r \\ \varepsilon_t^s \\ \varepsilon_t^e \end{pmatrix} \quad \text{at time step } t, \tag{13}$$

where the sentiment variable s_t enters the model after y, p, m, i and r. Consequently, news sentiment is assumed to be influenced by output, price, money and the interest rate. Then, the exchange rate is driven by all the variables including news sentiment.

Evaluation

In this section, we estimate the aforementioned VECM as follows: we first check for the validity of the assumptions. Second, we present impulse response functions for the classical overshooting model, as well as

the extended model including news sentiment. Third, we present the forecasting error variance decomposition for both models and, finally, we discuss our results.

Financial Time Series

The Dronbusch overshooting model consists of several macroeconomic variables: economic output Y_t, money supply M_t, prices P_t, short-term interest rates I_t, long-term interest rate R_t and the exchange rate E_t. In more detail, economic output Y_t is measured using the industrial production index, we use M1 as money supply M_t and the consumer price index for P_t. We ensure the assumption of a small country by following a U. K. perspective, whereas foreign variables are labeled with a star *. Furthermore, we calculate differences between U. K. and U. S. variables in order to reduce the dimensions of the VAR model. Accordingly, a shock in the home country shows the same effect as in the foreign country, which is a necessary but appropriate assumption given the low the number of observations (Heinlein & Krolzig 2012). A detailed overview of all relevant macroeconomic variables is given in Table 1. We feed the model with monthly data ranging from July 2003 to May 2012, giving a total of 107 observations. All financial data is provided by Thomson Reuters Datastream.

Table 1. Variables Entering the Time Series Model		
Variable	**Description**	**Specification as Entered in Model**
Y_t	Industrial Production Index	$y_t \quad := \quad \ln Y_t - \ln Y_t^*$
M_t	Money Supply M1	$m_t \quad := \quad \ln M_t - \ln M_t^*$
P_t	Consumer Price Index	$p_t \quad := \quad \ln P_t - \ln P_t^*$
I_t	3-Month T-Bill Yield	$i_t \quad := \quad I_t - I_t^*$
R_t	10-Year T-Bill Yield	$r_t \quad := \quad R_t - R_t^*$
E_t	Exchange Rate GBP/USD	$e_t \quad := \quad \ln E_t$

As part of our extended model, we need to include a news sentiment based on a suitable news corpus. Accordingly, all news originates from the *Thomson Reuters News Archive* for Machine Readable News. We choose this source of information since Thomson Reuters transmits independent, third-party announcements with shorter delay than printed media (MacGregor 2013; Paterson 2007) and can thus be be used to evaluate stock market reaction. All announcements provided by Reuters are extracted from between January 1, 2003 and May 31, 2012. Moreover, this information source enables us to effectively collect all exchange rate related announcements in the English language, while automatically omitting personal alerts or opinions, which might have a limited or even difficult to interpret information content. This is achieved by applying a set of filter criteria (Feuerriegel et al. 2014; Feuerriegel & Neumann 2013): (1) The language must be English. (2) The event type is *Story Take Overwrite* to guarantee that we do not yield an alert but the actual message. (3) Special types of announcements, such as alerts or personal opinions, might have limited relevance to changes in the exchange rate market and we want to exclude these. Thus, we omit announcements that contain specific words (*advisory, chronology, corrected, feature, diary, instant view, analysts view, newsmaker, corrected, refile, rpt, schedule, table, service, alert, wrapup, imbalance, update*) in their headline. (4) We use topic code *EXCA, US, GB* to filter announcements that deal with the GBP/USD exchange rate. (5) We exclude announcements addressing changes in prices to avoid simultaneity. (6) In order to remove white noise, we require announcements to contain at least 50 words. All in all, this gives a total of 3637 announcements related to the GBP/USD exchange rate.

Vector Error Correction Model

Before estimating the VECM, it is necessary to check for the validity of its assumptions and identify the specifications of the system. First, we test for a linear time trend in the underlying time series and conclude that only an unrestricted constant as a deterministic term is necessary in the model. Hence, we construct the

model only with a constant component and no time trend. Furthermore, we test the time series needs to be stationary through the augmented Dickey-Fuller (ADF) test. Its results in Table 2 show the outcome from the ADF test across different specifications. We conclude that all time series are integrated of order one, except the sentiment time series, which is stationary. Calculating first differences results into stationary time series.

Table 2. Augmented Dickey-Fuller Test for Stationarity Indicating that All Time Series are Stationary Except News Sentiment

Variable	Deterministic Trend	Lags	Test Value	Critical Values		
				1 %	5 %	10 %
y	Constant	1	-0.505	-3.46	-2.88	-2.57
Δy	Constant	1	-9.435	-3.46	-2.88	-2.57
m	Constant	1	-1.359	-3.46	-2.88	-2.57
Δm	Constant	1	-5.532	-3.46	-2.88	-2.57
p	Constant	1	-0.440	-3.46	-2.88	-2.57
Δp	Constant	1	-7.051	-3.46	-2.88	-2.57
i	Constant	1	-1.617	-3.46	-2.88	-2.57
Δi	Constant	1	-7.456	-3.46	-2.88	-2.57
r	Constant	1	-1.982	-3.46	-2.88	-2.57
Δr	Constant	1	-7.500	-3.46	-2.88	-2.57
e	Constant	1	-1.857	-3.46	-2.88	-2.57
Δe	Constant	1	-5.564	-3.46	-2.88	-2.57
s	Constant	1	-6.712	-3.46	-2.88	-2.57
Δs	Constant	1	-12.202	-3.46	-2.88	-2.57

In the next step, we need to decide upon the number of lags. We thus utilize different information criteria, namely, the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SC), the Hannan-Quinn Information Criterion (HQ) and the Final Prediction Error (FPE) in order to determine the optimal lag structure. The outcomes in Table 3 suggest a lag length of one, four or eight depending on the information criteria. The suggested number of lags is not consistent and we avoid preferring one criterion over another; consequently, we also perform the Portmanteau test for autocorrelation (Hendry & Juselius 2001). This approach suggests setting the number of lags to four in each of the two overshooting models.

Table 3. Optimal Number of Lags n

Information Criterion	AIC	HQ	SC	FPE
Suggested Lags n	8	1	1	4

We investigate cointegration by performing a Johansen cointegration test with trace statistics. The results indicate two cointegration relationships in the classical overshooting model and three cointegration relationships in the extended model including news sentiment. In addition, we study three a further test statistics: the Portmanteau test for autocorrelation, the Jarque-Bera test for non-normality and the MARCH test for heteroskedasticity. The corresponding results are presented in Table 4. Based on the outcomes, we conclude that there is no evidence for autocorrelation and heteroskedasticity given the relatively high P-values. Due to the P-value of the Jarque-Bera test, we reject the null hypothesis that there is normality.
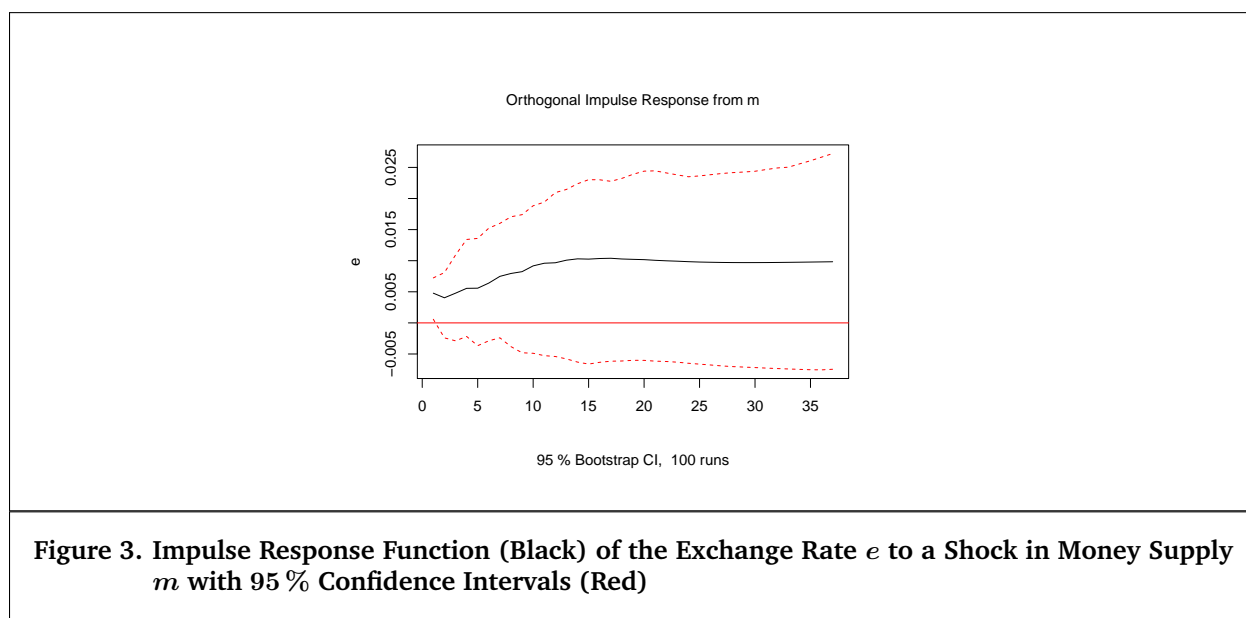
Table 4. Test Statistics for Autocorrelation, Non-Normality and Heteroskedasticity Indicating No Autocorrelation, Heteroskedasticity and Normality

Model	Portmanteau Test		Jarque-Bera Test		MARCH Test	
	Q_{16}	P-Value	JB_4	P-Value	$MARCH_5$	P-Value
Classical Overshooting Model	475.32	0.11	166.39	0.00	1769.41	0.46
Extended Model with News Sentiment	600.03	0.43	151.20	0.00	2772.00	1.00

We study the dynamics of the model by examining the *impulse response function* (IRF) of the two models. We thus compare the impulse response function of the classical overshooting model to the one of the extended

model in order to evaluate the response to a monetary shock. In addition, we consider the *forecast error variance decomposition* (FEVD) in order to investigate to which extent sentiment can explain the variance of the exchange rate. Due to the extensive nature of a VECM analysis, we can only present selected estimations of most interest.
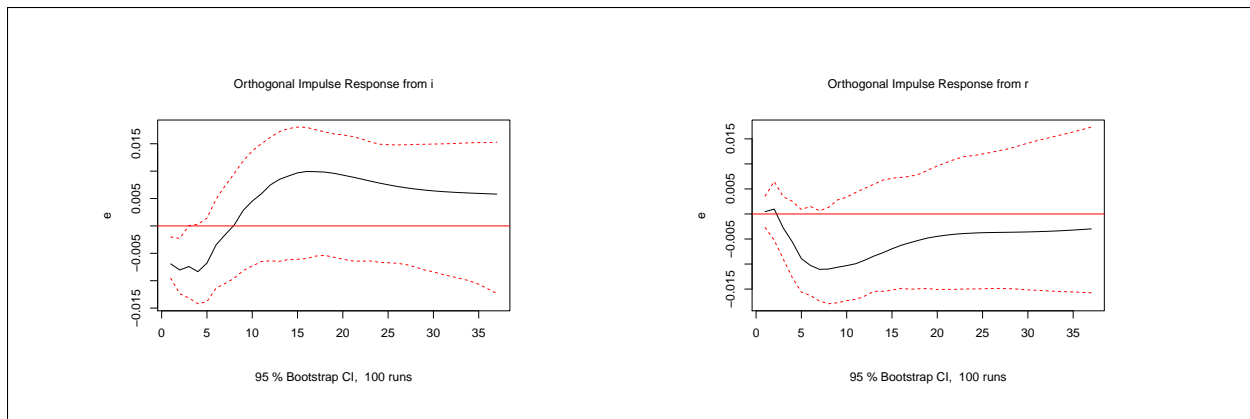
Impulse Response Functions of the Extended Model Including News Sentiment

We first analyze the behavior of the exchange rate e following a shock in the money supply m in Figure 3. We only present the impulse response function for the classical overshooting model, since there are hardly any observable differences regarding the monetary shock in the extended model. We note that the exchange rate e overshoots with news sentiment in response to a shock in the long-run interest rate r; this is the case for the classical overshooting model, as well as for the extended model. However, we observe a long-run depreciation that is a bit lower than in the classical overshooting model. Second, Figure 4 considers shocks in the short-run interest rate i and the long-run interest rate r. This can provide interesting insights, since interest rates are a common leverage from the toolkit of central banks. In addition, Figure 5 shows the response of the exchange rate with regard to a one-time shock of the news sentiment s. The exchange rate depreciates in the short-run straight after a positive shock in news. As a result, we find strong evidence that overshooting of the exchange rate occurs in response to a news shock. Surprisingly, the exchange rate appreciates and then gradually returns to its equilibrium after about ten months.
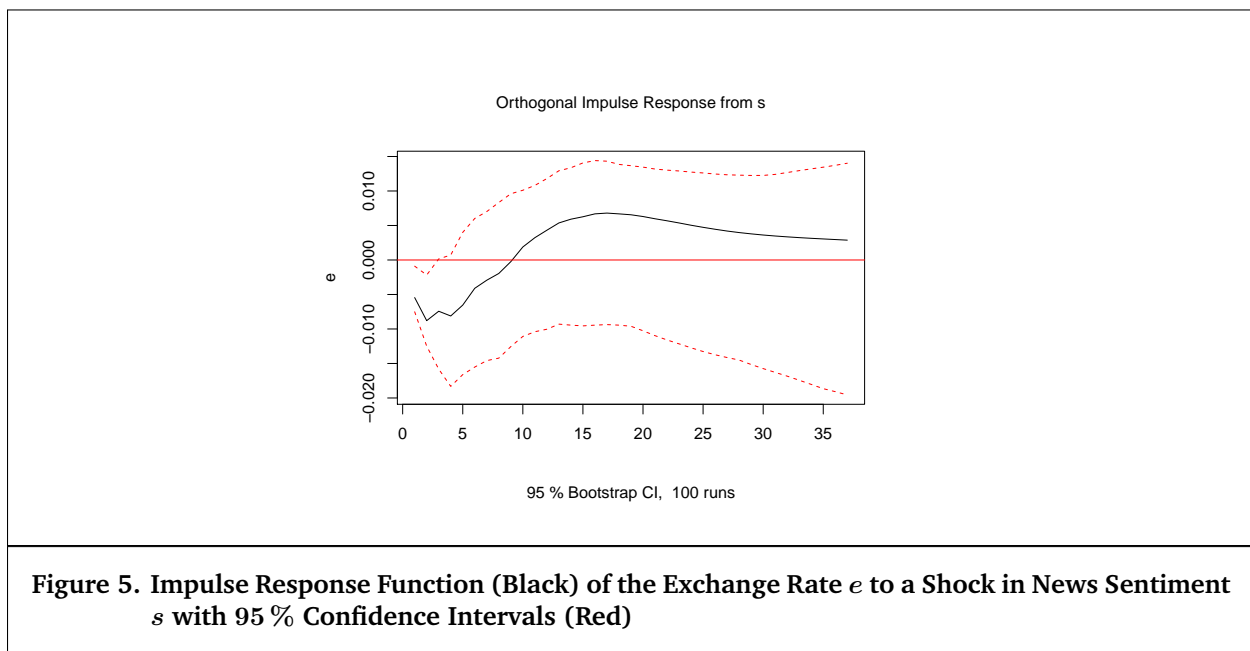

Figure 3. Impulse Response Function (Black) of the Exchange Rate e to a Shock in Money Supply m with 95 % Confidence Intervals (Red)

Forecast Error Variance Decomposition

We now turn to the most intriguing part and answer the question of to what degree can exchange rate behavior be explained through our news sentiment. For that reason, we perform a forecasting error variance decomposition. First of all, we observe that all variables in the model seem relevant and show a statistically significant impact. Furthermore, the output y and the long-run interest rate r play a considerable role in the long-run with less influence in the short-run. We can explain most of the variance by the exchange rate itself with a gradual decrease over time. Interestingly, our sentiment variable has a peak impact after two months of almost up to 11 percent, followed by a decrease to about 7 percent (see Table 5). This observation seems plausible, since news is of short-term nature (e. g. Galati & Ho 2003). We also notice that almost all of the variance regarding the sentiment variable is caught up with the variance related to the exchange rate. This

Figure 4. Impulse Response Function (Black) of the Exchange Rate e to a Shock in the Short-Run and Long-Run Interest Rate i and r with 95 % Confidence Intervals (Red)

Figure 5. Impulse Response Function (Black) of the Exchange Rate e to a Shock in News Sentiment s with 95 % Confidence Intervals (Red)

implies, that sentiment is valuable and has a significant impact on the behavior of the exchange rate and can help in explaining the movements of the exchange rate.

Theoretical Contribution and Managerial Implications

This section discusses our results and lists our main findings. We estimated a VECM to measure the reaction of the exchange rate between British Pound and U. S. Dollar following different monetary shocks. Shocks in both the goods markets and in the money market result in an overshooting of either the interest rate or the exchange rates. The overshooting is reasoned by the immediate reaction of the capital flows. In addition, we analyzed both the impulse response function and a forecasting error vector decomposition to complete our analysis: our results from the FEVD provide clear evidence that news can explain a significant portion of the exchange rate behavior. In addition, we are able to find the highest explanation power appear in the

Table 5. Forecast Error Variance Decomposition (in %) of the Exchange Rate Model Including News Sentiment

Month t	Industrial Production ε_t^y	Money Supply ε_t^m	Price Index ε_t^p	Short-Run Interest Rate ε_t^i	Long-Run Interest Rate ε_t^r	News Sentiment ε_t^s	Exchange Rate ε_t^e
1	0.01	6.05	6.10	12.73	0.06	7.88	67.16
2	0.5	4.01	11.92	11.56	0.12	10.97	60.88
3	2.02	3.97	12.02	10.76	0.57	10.41	60.23
6	5.96	4.71	13.58	8.46	6.45	8.23	52.59
12	9.49	9.32	14.36	6.26	13.08	4.99	42.50
24	7.73	16.98	9.62	12.98	11.49	7.09	34.12
36	6.52	21.69	8.36	13.94	10.17	6.81	32.50

Table 6. Forecast Error Variance Decomposition (in %) of the Classical Dornbusch Overshooting Model

Month t	Industrial Production ε_t^y	Money Supply ε_t^m	Price Index ε_t^p	Short-Run Interest Rate ε_t^i	Long-Run Interest Rate ε_t^r	Exchange Rate ε_t^e
1	0.01	4.87	7.26	13.61	0.03	74.21
2	0.5	3.41	13.27	12.08	0.11	70.58
3	2.12	3.39	13.25	10.83	0.52	69.87
6	7.80	3.68	14.02	7.31	7.61	59.58
12	15.13	8.17	11.61	7.62	15.84	41.63
24	14.75	16.25	6.86	15.74	15.00	31.38
36	13.89	19.72	5.42	16.60	14.69	29.68

short-run, which is in line with recent literature. Nevertheless, the impact of news remains visible during the entire time frame of up to 3 years. Hence, we can confirm our hypothesis A assuming news affects the exchange rate. The exchange rate depreciates in the short-run, which is equal to a strong domestic currency in the short-run.

More strikingly, the exchange rate overshoots in response to a positive shock in news sentiment. This implies a cognitive bias of investors processing news related to exchange rates. In terms of our earlier research questions, hypothesis B has been derived from the overshooting theory but needs to be rejected; the opposite effect, i. e. overshooting, is true. Consequently, we are able to derive the following managerial implications.

Implication 1: Policy makers, investors, and especially central bankers should consider the tone of news in their economic research.

Implication 2: News affects the exchange rate up to 15 months and longer. Hence, news has also a long-term influence. Consecutive and frequent analyses of news can support decision makers.

Implication 3: In response to a positive sentiment shock, the British Pound remains stronger than before. This finding may result in potential investment opportunities for investors.

Implication 4: Monetary approach models should include news content. News sentiment explains a significant part of the volatility of the exchange rate. Hence, using extended models may help to obtain more accurate results.

In conclusion, we are able to demonstrate a new path in behavioral economics and economic theory by combining information processing theory with classical economic theory.

Conclusion and Outlook

Exchange rates are extremely relevant in a globalized world since goods are traded internationally and thereby currencies are exchanged. The classical Dornbusch model is a thoroughly studied approach to explain the

behavior of exchange rates between two countries, but with controversial empirical outcomes. This is the reason why some scholars have extended the classical Dornbusch model to include news events. To our knowledge, they include the event itself but do not evaluate the textual news content, which is a frequent driver of prices.

As a contribution to theory and recent literature, this paper extends the classical overshooting model using a well-developed and insightful sentiment analysis from Information Systems research, which embraces the impacts of news disturbances in the model. The classical overshooting model acts as a referee to examine the impact of the extended model including news sentiment. Accordingly, we utilize a vector error correction model in order to measure the effects of a monetary shock in the U. K. and the U. S. to the GBP/USD exchange rate. We predominantly investigate the impulse response functions and forecasting error variance decomposition and conclude that the impulse response functions of the extended model including news sentiment hardly differ from the classical overshooting model, although the news sentiment shows a highly significant impact on the fluctuation of the exchange rate. This effect can be up to almost 11% of the forecasting error variance decomposition. More strikingly, we find empirical evidence of an cognitive bias of investors: a shock in news sentiment leads to an overshooting in exchange rates. It is worth noting that sentiment analysis as an methodology from Information Systems research provides added value to macroeconomic theory and can explain a significant portion of the underlying model.

In future work, we will advance the above implementation in two directions. First, we will estimate further model specifications to analyze the robustness of the results, since a VECM estimation is reasonably sensitive to its specifications. Second, it may be of additional value to derive a short-run and long-run restriction matrix based on further economic theory.

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