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Hartmann, Daniel and Pierdzioch, Christian

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Daniel Hartmann and Christian Pierdzioch

Abstract

Empirical evidence suggests that the link between exchange rate movements and stock returns may be nonlinear. This evidence could reflect fundamental economic effects like, for example, transaction costs in international goods market arbitrage. It could also reflect market inefficiencies if investors could exploit the nonlinearity to systematically improve the performance of simple trading rules. Using monthly data for major North-American and European industrial countries for the period 1973-2006, we found that it would have been difficult for an investor to use information on nonlinearities to improve the performance of a simple trading rule based on out-of-sample forecasts of stock returns.

Keywords: Stock returns, exchange rate movements, nonlinearities

JEL classification: C53, E44, F37

Addresses:

Daniel Hartmann
Saarland University
Department of Economics
Email: da.hartmann@mx.uni-saarland.de

Christian Pierdzioch
(corresponding author)
Saarland University
Department of Economics
Email: c.pierdzioch@mx.uni-saarland.de

P.O.B. 15 11 50
66041 Saarbruecken
Germany
Phone: +49-681-302-58195
Fax: +49-681-302-58193

1. Introduction

Research on the link between stock returns and exchange rate movements has a long tradition in the international finance literature (Adler and Dumas 1984). In the earlier literature, researchers have reported that this link is small and hardly significant (Jorion 1990, Griffin and Stulz 2001). In recent years, however, researchers have documented that the link between stock returns and exchange rate movements is nonlinear (Di Iorio and Faff 2000, Bartram 2004). Such a nonlinear link is consistent with, for example, models featuring transaction costs in international goods market arbitrage and sunk costs of market entry (Krugman 1989, Baldwin and Lyons 1994). Transaction costs and sunk costs of market entry imply that only large exchange rate movements affect market structure and, thereby, firms' market value. Empirical evidence of nonlinear exchange rate dynamics consistent with such models has been reported, for example, by Taylor and Peel (2000) and Taylor et al. (2001).

Our contribution to the literature is that we studied the nonlinear link between stock returns and exchange rate movements from an investor's perspective. We focused on a nonlinearity that arises because the link between stock returns and large exchange rate movements is different from the link between stock returns and small exchange rate movements. We analyzed whether an investor could have used information on a nonlinear link to forecast stock returns out-of-sample and to implement a simple trading rule. Taking an investor's perspective is interesting because a nonlinear link between stock returns and exchange rate movements need not necessarily reflect fundamental economic forces like, for example, transaction costs in international goods market arbitrage. A nonlinear link could also indicate market inefficiencies if an investor could use them to systematically improve out-of-sample forecasts of stock returns and the performance of a simple trading rule.

In order to compute out-of-sample forecasts of stock returns and to study the performance of a simple trading rule, we used the recursive modeling approach developed by Pesaran and Timmermann (1995, 2000). Their recursive modeling approach accounts for the fact that an investor, in real time, must forecast stock returns under conditions of model uncertainty. In real time, an investor does not know whether small and large exchange rate movements should be included in the optimal forecasting model, nor does the investor know the true parameters of the optimal model. The recursive modeling approach also makes it easy to test for an investor's market timing ability and to study, in terms of an investor's terminal wealth and Sharpe's ratio, the economic significance of accounting for a nonlinear link between stock returns and exchange rate movements.

Using monthly data for major North-American and European industrial countries for the period 1973-2006, we report evidence of a nonlinear link between stock returns and exchange rate movements in the cases of France, Germany, Italy, and the United States. Consistent with theories of, for example, transaction costs in international goods market arbitrage, large exchange rate movements tend to be more often included in the optimal model for forecasting one-month ahead stock returns than small exchange rate movements. Also consistent with theories that trace nonlinearities in exchange rates to fundamental economic forces like transaction costs rather than market inefficiencies, we found that accounting for a differential impact of large and small exchange rate movements on stock returns has only a negligible effect on an investor's market-timing ability. In addition, it would have been difficult for an investor, in real time, to use information on a nonlinear link between stock returns and exchange rate movements to improve the performance of a simple trading rule based on out-of-sample forecasts of stock returns.

In Section 2, we describe the recursive modeling approach we used to study the nonlinear link between stock returns and large and small exchange rate movements. In Section 3, we describe our data. In Section 4, we lay out our results, and we summarize the results of robustness checks. In Section 5, we conclude.

2. The Recursive Modeling Approach

In a first step, we describe how an investor can use the recursive modeling approach to forecast stock returns. In a second step, we describe how the recursive modeling approach can be used to test for market timing. In a third step, we describe how the recursive modeling approach can be used to measure the performance of a simple trading rule.

2.1 Recursive Forecasting of Stock Returns

We considered an investor who uses a set of K predictor variables to forecast one-month ahead stock returns. The problem of the investor is to decide how to combine the K predictor variables to forecast stock returns. Hence, in every month, the investor must reach a decision under uncertainty about the optimal forecasting model. As in Pesaran and Timmermann (1995, 2000), the investor solves this decision problem by using a recursive modeling approach. This approach requires that the investor systematically searches in every month over all possible 2^K forecasting models to identify the optimal forecasting model. As time progresses, the investor recursively restarts this search and updates the optimal forecasting model.

In order to conduct this recursive search and updating process in an efficient and timely manner, the investor considers linear regression models of the format $r_{t+1} = X_{t,i}\beta_i + \varepsilon_{t+1,i}$. Here, r_{t+1} denotes the vector of (excess) returns from the first month in the sample up to and including month *t*+1, β_i denotes the vector of coefficients to be estimated, $i = 1,2,...$ denotes the model *i*, $\varepsilon_{t+1,i}$ denotes a stochastic disturbance term, and $X_{t,i}$ denotes the set of predictor variables under model *i*. We assume that the set of predictor variables always includes a constant.

In order to identify the optimal forecasting model among the 2^K forecasting models estimated in month *t*, the investor uses the Adjusted Coefficient of Determination (ACD) as a model-selection criterion. Expressing the variables in deviation from mean, the ACD is defined as $ACD_{t,i} = 1-[1-(r'_{t+1}\, r_{t+1} - e'_{t,i}\, e_{t,i})/(r'_{t+1}\, r_{t+1})](T_t - 1)/(T_t - k_{t,i})$ where $e_{t,i}$ denotes the estimated residuals under model *i* in month *t*, T_t denotes the number of observations available in month *t*, and $k_{t,i}$ denotes the number of regressors considered under model *i* in month *t*. The optimal forecasting model is the one that maximizes the ACD.

2.2 Market Timing

We used the tests developed by Cumby and Modest (1987) and Pesaran and Timmermann (1992) to test for an investor's market-timing ability. We implemented the Cumby-Modest test by defining a dummy variable, D_t, that assumes the value one when the forecast of stock returns implied by the recursive modeling approach is positive, and zero otherwise. We used this dummy variable to estimate the regression equation $r_{t+1} = \beta_0 + \beta_1 D_t + \varepsilon_t$, where ε_t denotes a stochastic disturbance term and, from now on, r_{t+1} denotes a scalar. A significant coefficient, β_1, indicates market timing.

The test developed by Pesaran-Timmermann is a nonparametric test of market timing. The null hypothesis is that there is no information in the forecasts of stock returns over the sign of subsequent realizations of stock returns. The test can be used to analyze whether there is information in the forecasts of stock returns, $\hat{r}_{t+1}$, with regard to the sign of one-month ahead realizations of stock returns, r_{t+1}. In a first step, one computes the probabilities $P_1 = P(\hat{r}_{t+1} > 0)$, $P_2 = P(r_{t+1} > 0)$ and $P = T^{-1}\sum_{t=1}^{T} Z_t$, where T denotes the sample size and $Z_t = 1$ if $\hat{r}_{t+1} \times r_{t+1} > 0$, and zero otherwise. In a second step, one uses $P^* = P_1 \times P_2 + (1 - P_1) \times (1 - P_2)$ to compute $PT = (P - P^*) \times (\mathrm{Var}(P) - \mathrm{Var}(P^*))^{-1/2}$, where $\mathrm{Var}(P)$ denotes the variance of P. The test, PT, has an asymptotic standardized normal distribution.

2.2 A Simple Trading Rule

The recursive modeling approach implies a sequence of optimal forecasting models, and a sequence of optimal one-month-ahead stock-return forecasts. The investor can use the forecasts to set up a simple trading rule. We considered an investor who invests in stocks if the one-month-ahead forecast implied by the optimal forecasting model is positive. Otherwise, the investor invests in bonds. Depending on the sequence of investments chosen by the investor, the financial wealth of the investor changes over time. In order to model how the financial wealth of the investor changes over time, we introduce some notation. Our notation follows Pesaran and Timmermann (1995).

We denote the financial wealth of the investor at the end of month *t* by W_t, the price of stocks at the end of month *t* by P_t, and the dividends paid during month *t* by D_t. The number of stocks held by the investor at the end of month *t* is given by N_t, and the investor's position in bonds is given by B_t. We assume that trading in stocks and bonds involves transaction costs that are (i) constant through time, (ii) the same for buying and selling stocks and bonds, and (iii) proportional to the value of a trade. The investor that we consider does not make use of short selling, nor does our investor use leverage when deciding on the optimal investment strategy. We denote the percentage transaction costs on stocks and bonds by c_1 and c_2, respectively. Taking account of transaction costs, the investor buys in month *t* a number of stocks of $N_t = (1-c_1)W_t / P_t$ if $\hat{r}_{t+1} > 0$, and a number of bonds of $B_t = (1-c_2)W_t$ if $\hat{r}_{t+1} < 0$.

The investor analyzes the optimality of an investment in stocks and bonds made in month *t*+1 based on the forecast of stock returns for month *t*+2. Four different cases have to be considered:

- Case 1: The investor invested in stocks in month *t*+1, and reinvests cash dividends in month *t*+2. In this case, we have $\hat{r}_{t+1} > 0$ and $\hat{r}_{t+2} > 0$, $N_{t+1} = N_t + N_t D_t (1-c_1)/P_{t+1}$, and $B_{t+1} = 0$.
- Case 2: The investor invested in stocks in month *t*+1, but buys bonds in month *t*+2. In this case, we have $\hat{r}_{t+1} > 0$ and $\hat{r}_{t+2} < 0$, $N_{t+1} = 0$, and $B_{t+1} = (1-c_2)[(1-c_1)N_t P_{t+1} + N_t D_{t+1}]$.
- Case 3: The investor invested in bonds in month *t*+1, but buys stocks in month *t*+2. In this case, we have $\hat{r}_{t+1} < 0$ and $\hat{r}_{t+2} > 0$, $N_{t+1} = (1-c_1)B_t(1+R_t)/P_{t+1}$, and $B_{t+1} = 0$.
- Case 4: The investor invested in bonds in month *t*+1, and continues to invest in bonds in month *t*+2. In this case, we have $\hat{r}_{t+1} < 0$ and $\hat{r}_{t+2} < 0$, $N_{t+1} = 0$, and $N_{t+1} = (1-c_2)B_t(1+R_t)$.

The dynamics of the financial wealth of the investor can be described in terms of the budget constraint $W_{t+2} = N_{t+1}(P_{t+2} + D_{t+2}) + B_{t+1}(1+R_{t+1})$, where R_t denotes the risk free interest rate on bonds.

We used the investor's terminal wealth, W_T, and Sharpe's ratio (Sharpe 1966) to measure the performance of the investor's simple trading rule. We computed Sharpe's ratio as $SR = (r_T - R_T) / SD$, where SR denotes Sharpe's ratio, r_T denotes returns at the end of the investment horizon, T, and SD denotes the standard deviation of portfolio returns.

3. The Data

Our sample consists of the following North-American and European countries: Canada, France, Germany, Italy, United Kingdom, and United States. Our sample covers the period 1973/1–2006/12. Most of the data we used in our empirical analyses are from Thomson Financial Datastream. (More details on the data, including data sources, are given at the end of the paper). In order to measure the development of the stock markets, we used end-of-month data on the market price index. We then computed the stock returns, added dividends, and subtracted a short-term interest rate in order to calculate excess stock market returns.

We used the data on nominal effective exchange rates compiled by the Bank for International Settlements (2006) to measure the exchange rate. In order to compute exchange rate movements (NEER), we computed the percentage change in the exchange rate. The variable NEER_BIG (NEER_SMALL) is equal to NEER if exchange rate movements were larger (smaller) than 0.5 times its recursively estimated unconditional standard deviation, and zero otherwise (Bartram 2004). In order to set up the recursive estimation, we used data from 1972/1 up to the month in which NER is observed. The variables NEER_BIG and NEER_SMALL capture a nonlinear link between exchange rate movements and stock returns.

We used the following macroeconomic and financial variables as control variables:

1) The stochastically detrended short-term interest rate, defined as the difference between the short-term interest rate and its 12-month moving average (Rapach et al. 2005). We used a three-months treasury bill rate as our short-term interest rate. In case a three-months treasury bill rate was not available for a country, we used a money market rate.

2) The term spread, defined as the difference between a long-term government bond yield and a short-term interest rate. The term spread has been considered by, for example, Chen et al. (1986) as a predictor of stock returns.

3) The inflation rate, defined as the change in the natural logarithm of the consumer price index. The inflation rate can be used as a measure of monetary conditions and business-cycle fluctuations (Chen et al. 1986). We accounted for a publication lag of one month.

4) The change in the natural logarithm of industrial production. Various studies of stock return predictability have used this variable to control for the stance of the business cycle (Rapach et al. 2005). We accounted for a publication lag of one month.

5) The dividend yield. Shiller (1984) and many others have analyzed the forecasting ability of the dividend yield for stock returns.

We used the twelve-month moving averages of the change in the natural logarithm of industrial production and the inflation rate to minimize the effects of data revisions on our results.

4. Results

We report in Panel A of Table 1 how often the predictor variables NEER, NEER_BIG, and NER_SMALL are included in the optimal forecasting models. In the cases of France, Germany, Italy, and the United States, there is evidence of nonlinearities in the link between stock returns and exchange rate movements. Consistent with models that feature, for example, transaction costs in international goods market arbitrage and sunk costs of market entry, large exchange rate movements tend to be a more important predictor variable than small exchange rate movements. In contrast, in the case of Canada and the United Kingdom, there is also evidence of nonlinearities, but the recursive modeling approach selects the predictor variable NER_SMALL more often than the predictor variable NEER_BIG.

— Insert Table 1 about here. —

In Panel B of Table 2, we report the results of tests for market timing. The tests do not yield significant results. We conclude, therefore, that accounting for a nonlinear link between stock returns and small and large exchange rate movements does not improve an investor's market timing ability. One interpretation of this result is that the evidence of a nonlinear link between stock returns and exchange rate movements reflects fundamental economic factors and not market inefficiencies.

— Insert Table 2 about here. —

The results summarized in Table 2 confirm this interpretation. Irrespective of the level of transaction costs, the Sharpe's ratios and investor's terminal wealth are hardly affected by using the predictor variables NEER_BIG and NER_SMALL rather than the predictor variable NEER. The Sharpe's ratio and investor's terminal wealth are more or less the same for a forecasting model that feature the predictor variables NEER_BIG and NER_SMALL rather than NEER even in the cases of France, Germany, Italy, and the United States. These are the countries for which the recursive modeling approach has detected, consistent with theories of transaction costs in international goods market arbitrage, evidence of a nonlinear link between stock returns and large and small exchange rate movements.

We performed four robustness checks to analyze whether the robustness of our results to alternative specifications of the recursive modeling approach. (The results are available from the authors upon request.) First, we changed the definition of the predictor variables NEER_BIG and NEER_SMALL. To this end, we set the predictor variables NEER_BIG (NEER_SMALL) to NEER if exchange rate movements were larger (smaller) than its recursively estimated unconditional standard deviation, and zero otherwise. Second, we used a twelve-month unweighted historical moving average of the predictor variables NEER_BIG and NEER_SMALL as predictor variables for stock returns. Third, we used a rolling rather than a recursive modeling approach. To this end, we defined a rolling estimation window of length five years. Using a rolling estimation window renders it possible to account for potential structural breaks in the link between stock returns and exchange rate movements. Finally, we used other model-selection criteria than ACD to identify the optimal forecasting model. We used the Akaike Information Criterion, a Direction-of-Change

Criterion, and a Wealth-Based Criterion. The latter selects the forecasting model that would have generated in-sample the largest wealth if the investor would have used the simple trading rule laid out in Section 2.2 to allocate wealth across stocks and bonds. The results of all four robustness checks corroborated our main result that it would have been difficult for an investor to use information on nonlinearities in the link between stock returns and large and small exchange rate movements to improve the performance of a simple trading rule based on out-of-sample forecasts of stock returns.

6. Conclusions

The results of our empirical analysis suggest that it was hardly possible for investors investing in major North-American and European countries to exploit a nonlinear link between stock returns and small and large exchange rate movements. One interpretation of our finding is that it indicates that such a nonlinear link can be explained in terms of fundamental economic factors rather than market inefficiencies. Several different economic theories can be used to identify such fundamental economic factors. In recent years, theories that emphasize the role played by transaction costs in international goods market arbitrage and sunk costs of market entry have received considerable attention in the empirical literature. While our finding does not lend direct support to such theories, the recursive modeling approach we used in our research could be refined in future research to directly test the implications of such theories.

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Data Appendix

Most of the data used in this paper are extracted from Thomson Financial Datastream. We report the Datastream codes for the six countries we analyzed: Canada (CN), France (FR), Germany (BD), Italy (IT), the United Kingdom (UK), and the United States (US).

- Short-term interest rate: CNI60C.., FRI60B.., BDI60B.., ITI60B.., UKI60C.., USI60C…
- Long-term government bond yield: CNI61…, FRI61…, BDI61…, ITI61…, UKI61…, USI61….
- Consumer price index: CNI64…F, FRI64…F, BDOCP009F, ITI64…F, UKI64…F, USI64…F.
- Industrial production: CNI66..IG, FRI66..IG, BDI66..IG, ITI66..IG, UKI66..IG, USI66..IG.
- Stock price index: TOTMKCN(PI), TOTMKFR(PI), TOTMKBD(PI), TOTMKIT(PI), TOTMKUK(PI), TOTMKUS(PI).
- Dividend yield: TOTMKCN(DY), TOTMKFR(DY), TOTMKBD(DY), TOTMKIT(DY), TOTMKUK(DY), TOTMKUS(DY).

As our measure of the exchange rate we used the data on nominal effective exchange rates compiled by the Bank for International Settlements (2006). The series codes are: NNCA (Canada), NNFR (France), NNDE (Germany), NNIT (Italy), NNGB (the United Kingdom), NNUS (the United States).

Tables and Figures

Table 1 – Results of recursive forecasting of stock returns, 1973-2006

Panel A: Inclusion of variables in optimal forecasting models in percent

	NEER	NEER_BIG	NEER_SMALL
Canada	2.02	11.53	52.45
France	25.07	44.67	14.12
Germany	30.84	30.84	6.05
Italy	48.13	51.30	37.46
UK	1.44	1.15	13.54
USA	53.31	53.31	2.31

Panel B: Tests of market timing

	Model with NEER		Model with NEER_BIG and NEER_SMALL	
	CM	PT	CM	PT
Canada	0.59	0.84	0.65	0.84
France	-1.01	-0.34	-1.03	-0.54
Germany	-0.73	-0.99	-0.75	-0.88
Italy	-1.98	-1.26	-1.71	-0.90
UK	0.15	0.55	-0.18	0.11
USA	0.35	-0.75	0.28	-0.93

Note: NEER denotes the nominal effective exchange rate, and NEER_BIG (NEER_SMALL) denotes a variable that is equal to NEER if exchange rate returns were larger (smaller) than 0.5 times its recursively estimated unconditional standard deviation, and zero otherwise. In Panel B, we present results of tests of market timing. CM denotes the test developed by Cumby and Modest (1987). This test requires estimating a regression of realized stock returns on a constant and a dummy variable that assumes the value one if the forecast of stock returns is positive, and zero otherwise. We report the t-statistics of the dummy variable. The t-statistics are based on heteroskedasticity consistent standard errors. PT denotes the nonparametric tests for market timing developed by Pesaran and Timmermann (1992). The Pesaran-Timmermann test has asymptotically a standard normal distribution.

Table 2 – Performance of a simple trading rule, 1973-2006

PANEL A: Model with NEER

	Sharpe's ratio			Terminal wealth		
	Transaction costs			Transaction costs		
	Zero	Medium	High	Zero	Medium	High
Canada	0.26	0.25	0.23	2705	2151	1853
France	0.21	0.20	0.20	6139	5583	5152
Germany	0.12	0.10	0.09	810	609	485
Italy	0.16	0.16	0.15	4172	3661	3283
UK	0.22	0.19	0.17	1180	815	678
USA	0.23	0.20	0.17	1706	1071	755

PANEL B: Model with NEER_BIG and NEER_SMALL

	Sharpe's ratio			Terminal wealth		
	Transaction costs			Transaction costs		
	Zero	Medium	High	Zero	Medium	High
Canada	0.27	0.24	0.21	2781	1884	1382
France	0.21	0.20	0.20	6042	5545	5169
Germany	0.12	0.10	0.09	810	616	496
Italy	0.16	0.15	0.15	4105	3469	3019
UK	0.21	0.17	0.15	1054	701	561
USA	0.23	0.19	0.16	1632	1012	706

Note: NEER denotes the nominal effective exchange rate, and NEER_BIG (NEER_SMALL) denotes a variable that is equal to NEER if exchange rate returns were larger (smaller) than 0.5 times its recursively estimated unconditional standard deviation, and zero otherwise. For switching between shares and bonds, the investor uses information on the optimal one-month-ahead stock-return forecasts implied by the optimal forecasting model. When the optimal one-month-ahead stock-return forecast is positive (negative), the investor only invests in stocks (bonds), not in bonds (stocks). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for stocks and bonds, respectively. Initial wealth is 100.