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Forecasting foreign exchange rates using idiosyncratic volatility ☆

Hui Guo [a,*], Robert Savickas [b,1]

[a] College of Business Administration, University of Cincinnati, Cincinnati, OH 45221, USA
[b] Department of Finance, George Washington University, 2023 G Street, N.W., Washington, DC 20052, USA

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Abstract

Average idiosyncratic stock volatility forecasts the bilateral exchange rates of the US dollar against major foreign currencies in and out of sample. The US dollar tends to appreciate after an increase in US idiosyncratic volatility. Similarly, ceteris paribus, German and Japanese idiosyncratic volatilities positively and significantly correlate with future US dollar prices of the Deutsche mark and the Japanese yen, respectively. Our results suggest that exchange rates are predictable.

JEL classification: F31; G1

Keywords: Exchange rate predictability; Average idiosyncratic stock volatility; Monetary model; Out-of-sample forecast; Bootstrap; Data mining

1. Introduction

This paper investigates whether financial variables – which have been commonly used as predictors of monetary fundamentals, stock returns, or bond returns – forecast exchange rates. Our motivations are twofold. First, in monetary models advanced by Bilson (1978), Dornbusch (1976), Frenkel (1976), and Mussa (1976), exchange rates are equal to the sum of expected future monetary fundamentals. Therefore, a financial variable might explain exchange rates because of its influence on fundamentals. Second, because stocks, bonds, and foreign exchanges are susceptible to the same macroeconomic risk (e.g., Goodhart et al., 1993; Almeida et al., 1998; and Andersen et al., 2004), the expected risk premia that investors require for holding these assets might closely relate to each other. Thus, a financial variable that is a proxy for stock or bond premia might forecast exchange rates as well. The main concern of this study is empirical evidence of exchange rate predictability and we do not try to provide a formal test of these two hypotheses, however.

We mainly focus on the bilateral exchange rates of the US dollar against currencies of other G7 countries. Financial variables from both US and a foreign country are used to forecast the exchange rate of the foreign country's currency against the US dollar. The variables considered here include the default premium, the term spread, the stochastically detrended risk-free rate, the excess stock market return, aggregate stock market volatility, and average idiosyncratic stock volatility. Our choice reflects the fact that these variables are the most widely used predictors of stock returns, bond returns, or monetary fundamentals in empirical studies (e.g., Campbell, 1987; Fama and French, 1989; Barro, 1990; Bernanke and Blinder, 1992; Campbell et al.,

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* Corresponding author. Tel.: +1 513 556 7077; fax: +1 513 556 0979.
E-mail addresses: hui.guo@uc.edu (H. Guo), Savickas@gwu.edu (R. Savickas).
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1997; Campbell et al., 2001, hereafter CLMX; Goyal and Santa-Clara, 2003; Stock and Watson, 2003; Guo and Whitelaw, 2006 and Guo and Savickas, 2007). In the empirical analysis, we assume that changes in log nominal exchange rates are a linear function of lagged financial variables and use Krolzig and Hendry's (2001) general-to-specific model selection procedures to obtain a parsimonious forecasting model.

We document a strong relation between idiosyncratic stock volatility (IV) and exchange rates. US IV forecasts the US dollar rates against most of foreign currencies. A relatively high level of US IV is usually associated with a future appreciation in the US dollar. Similarly, ceteris paribus, German IV and Japanese IV are positively and significantly correlate with future US dollar prices of the Deutsche mark and the Japanese yen, respectively. The pattern is much less consistent for the other financial variables, however: They forecast some exchange rates but not others. For robustness, we also conduct out-of-sample forecast tests and find that our forecasting models always outperform the benchmark of a random walk model.

Our findings are in sharp contrast with those obtained using monetary fundamentals as predictive variables. In an influential paper, Meese and Rogoff (1983) show that a naïve random walk model outperforms monetary fundamentals in the out-of-sample forecast of nominal exchange rates. The Meese and Rogoff result is strikingly robust after over 20 years of fresh data and intensive academic research. Most of the subsequent studies confirm that it is difficult to outperform the random walk model of exchange rates. The difference between our paper and the earlier studies might reflect the fact that financial variables are a better measure of business conditions than are monetary fundamentals or the fact that financial variables move closely with the conditional foreign exchange risk premia.

Evans and Lyons (2005a,b) show that order flow forecasts exchange rates possibly because it contains information about future fundamentals. Clarida and Taylor (1997) and Boudoukh et al. (2005) find that interest rate differentials have some out-of-sample predictive power. Hong and Lee (2003) and Sweeney (2006) find evidence of exchange rate predictability by using nonlinear time series models and panel data, respectively. We complement their empirical findings by proposing idiosyncratic volatility as a new predictor of exchange rates.

The remainder of the paper is organized as follows. We explain the empirical specification in Section 2 and discuss data in Section 3. We present the in-sample forecasting results for exchange rates in Section 4 and investigate the out-of-sample forecast in Section 5. We offer some tentative explanations and concluding remarks in Section 6.

2. The empirical specification

In the empirical analysis, we use a linear forecasting model for the change in log nominal exchange rates of a foreign country's currency against the US dollar, Δs_{t+1}:

$$\Delta s_{t+1} = \alpha + \beta X_t + \zeta_{t+1}, \tag{1}$$

where α is a constant, β is a vector of coefficients, X_t is a vector of lagged financial variables, and ζ_{t+1} is an error term that is uncorrelated with X_t.[2] The vector X_t includes various lags of both US and the foreign country's financial variables. It also includes lags of the dependent variable. Eq. (1) is a single equation VAR (vector autoregressive) mode1. In general, ζ_{t+1} can be serially correlated and heteroskedastic. The OLS estimators of α and β are consistent; and we can correct for the autocorrelation and heteroskedasticity in the error term by using the Newey-West standard error.

We can show that Eq. (1) is a reduced form of monetary models.[3] Intuitively, because exchange rates are equal to the sum of expected future fundamentals, a financial variable might explain exchange rates through its influence on fundamentals. Alternatively, a financial variable that forecasts stock or bond returns might also forecast exchange rates because the expected risk premia that investors require for holding stocks, bonds, and foreign exchanges might closely relate to each other. Following these conjectures, we consider only the financial variables that have been commonly used in the forecast of monetary fundamentals, stock returns, or bond returns.

One can formally test a structural monetary model instead of estimating a reduced form. While such an exercise is potentially interesting, it does not shed much new light on monetary models. For example, if the poor performance of monetary models reflects an omitted variable problem (e.g., Meese, 1990) or data revision (e.g., Faust et al., 2003), the new test will likely reject monetary models for the same reasons. In contrast, the omitted variable problem and data revision do not directly affect the reduced form in Eq. (1). Therefore, in this paper we focus mainly on exchange rate predictability and do not attempt to test a structural model of exchange rates.

Existing economic theory does not indicate which financial variables forecast exchange rates. To alleviate the omitted variable problem, we include most of commonly used predictors of monetary fundamentals, stock returns, or bond returns in our single equation VAR model. Many authors, however, have argued that it is desirable to have a parsimonious model, especially in the out-of-sample forecast. We address this issue by using Krolzig and Hendry's (2001) computer-automated general-to-specific (*PcGets*) model selection procedures. The main idea of *PcGets* is as follows. We start from a single equation VAR model, as in Eq. (1). We then use standard testing procedures to eliminate statistically insignificant variables, with diagnostic tests checking the validity of reductions, ensuring a congruent final selection. In their Monte Carlo experiments,

[2] Adding a linear time trend to Eq. (1) does not change our results in any qualitative manner.

[3] We provide the deviation in an appendix in an earlier draft, which is available on request.

Krolzig and Hendry show that *PcGets* recovers the DGP (data generating process) specification from a general model with size and power close to commencing from the DGP itself. Because our forecasting variables are empirically motivated, data mining is an important concern over model selection procedures. As a robustness check, we also investigate whether the selected final models forecast exchange rates out-of-sample.

3. Data

We obtain quarterly end-of-period nominal exchange rate data from IFS (International Financial Statistics). Exchange rates are denoted as the prices of the US dollar in foreign currencies, e.g., the Deutsche mark/US dollar rate. Data span the period 1973:Q1–1998:Q4 for euro area countries and span the period 1973:Q1–2003:Q4 for non-euro area countries. Many authors, e.g., Meese and Rogoff (1983) and Mark (1995), find that exchange rate predictability increases with forecasting horizons. To address this issue, we analyze non-overlapping data for three different horizons – quarterly, semi-annual, and annual. This analysis also serves as a robustness check: We expect that the model selection procedure results in similar final models across forecasting horizons.

Panel A of Table 1 provides summary statistics of quarterly changes in log nominal exchange rates for six other G7 countries over the period 1973:Q1–1998:Q4. Exchange rates exhibit a trend for some currencies (line 1). For example, the Japanese yen has appreciated about 4% annually, while the Italian lira has depreciated about 4% per year. Except for the Canadian dollar, exchange rates are quite volatile, with the quarterly standard deviation around 6% (line 2). The autocorrelation is usually moderate (line 3). The Canadian dollar rate is essentially uncorrelated with the other exchange rates; however, the other exchange rates are closely correlated among themselves, with an average correlation coefficient about 0.66.[4] As we show in Section 4, the Canadian dollar rate also behaves quite differently from other exchange rates in the forecasting regression. We find similar results for semi-annual and annual data; for brevity, they are not reported here but are available on request.

Panel B of Table 1 provides summary statistics for the US forecasting variables over the period 1973:Q1–1998:Q4.[5] The default premium (DEF) is the difference between yields on Baa- and Aaa-rated corporate bonds obtained from Standard and Poor's. The term premium (TERM) is the difference between yields on 10-year Treasury bonds and three-month Treasury bills obtained from the Federal Reserve Board. The stochastically detrended risk-free rate (RREL) is the difference between the one-month risk-free rate and its average in the previous 12 months, and we obtained the monthly risk-free rate from CRSP (Center for Research of Security Prices). The excess stock market return (ERET) is the difference between the CRSP value-weighted stock market return and the CRSP risk-free rate. Following Merton (1980) and many others, we define realized aggregate stock market volatility (MV) as the sum of squared daily excess CRSP value-weighted market returns in a quarter. Lastly, as in Guo and Savickas (2007), average firm-level idiosyncratic volatility (IV) is defined as

$$IV_t = \sum_{i=1}^{N_t} \omega_{it}\left[\sum_{d=1}^{D_{it}} \eta_{id}^2 + 2\sum_{d=2}^{D_{it}} \eta_{id}\eta_{id-1}\right] \quad \text{and}$$

$$\omega_{it} = \frac{v_{it-1}}{\sum_{j=1}^{N_t} v_{jt-1}}, \tag{2}$$

where N_t is the number of stocks in quarter t, D_{it} is the number of trading days for stock i in quarter t, η_{id} is the idiosyncratic shock to the excess return on stock i in day d of quarter t, and v_{it-1} is the market capitalization of stock i at the end of quarter $t-1$. The idiosyncratic shock, r_{id}, is the residual from the regression of the excess return, er_{id} – the difference between the return on stock i and the risk free rate – on a constant and the excess stock market return, e_{md}.[6]

Ferson et al. (2003) caution that using persistent regressors can lead to spurious regressions, especially in the context of data mining. Panel B of Table 1 shows that except for the default premium, our forecasting variables are not highly persistent. For example, the autocorrelation coefficient is usually less than 0.9, which is considerably lower than that of the variables considered in Ferson et al. Also, the augmented Dick-Fuller test fails to reject the null hypothesis of a unit root process only for the default premium. The latter result might reflect the lack of power in the unit root test, however: The default premium is found to be stationary if we use a longer sample. Nevertheless, excluding the default premium from our forecasting models does not qualitatively change our main finding that exchange rates are predictable.

We also construct financial variables for other G7 countries in a way similar to their US counterparts. For the term premium and the stochastically detrended risk-free rate, we

[4] We find a similar pattern using data ending in 1996 – two years before the euro was adopted.

[5] Many authors have used the dividend yield to forecast stock returns. Lettau and Ludvigson (2001, 2002) also show that the consumption-wealth ratio is a strong predictor of stock returns as well as business investment. We do not consider these two variables here, however, because the dividend yield appears to be non-stationary and the consumption-wealth ratio contains information that is unavailable to investors at the time of forecast. Nevertheless, in an earlier version of this paper, we find that both variables have negligible forecasting power for exchange rates.

[6] We find that average industry-level idiosyncratic volatility (as constructed in CLMX) has predictive power for exchange rates similar to that of average firm-level idiosyncratic volatility. For brevity, we do not report the results using industry-level idiosyncratic volatility here but they are available on request.

Table 1
Summary statistics

	Canada	France	Germany	Italy	Japan	UK
Panel A changes in log nominal exchange rates						
Univariate statistics						
Mean	0.004	0.001	−0.006	0.010	−0.009	0.003
Standard deviation	0.021	0.060	0.064	0.057	0.063	0.054
Autocorrelation	0.040	0.165	0.096	0.171	0.135	0.153
Cross-correlation						
Canada	1.00					
France	0.03	1.00				
Germany	0.04	0.92	1.00			
Italy	0.04	0.80	0.72	1.00		
Japan	0.05	0.59	0.61	0.48	1.00	
UK	0.13	0.68	0.66	0.66	0.49	1.00
	DEF	TERM	RREL	MV	IV	ERET
Panel B US forecasting variables						
Univariate statistics						
Autocorrelation	0.90	0.78	0.72	0.52	0.83	0.04
Augmented Dick–Fuller test	−1.98	−3.43**	−2.69*	−6.74***	−4.22***	−5.43***
Cross-correlation						
DEF	1.00					
TERM	0.26	1.00				
RREL	−0.34	−0.62	1.00			
MV	0.17	−0.06	−0.12	1.00		
IV	0.11	−0.09	−0.09	0.76	1.00	
ERET	0.13	0.15	−0.26	−0.38	−0.18	1.00

Notes: The table reports summary statistics of quarterly changes in log nominal exchange rates of the US dollar in terms of major foreign currencies (panel A) and summary statistics of US financial variables (panel B) over the sample period 1973:Q1–1998:Q4. DEF is the yield spread between Baa- and Aaa-rated corporate bonds; TERM is the yield spread between 10-year Treasury bonds and three-month Treasury bills; RREL is the difference between the one-month risk-free rate and its average in the previous 12 months; MV is realized stock market volatility; IV is average firm-level idiosyncratic stock volatility; and ERET is the excess stock market return. We include a constant in the augmented Dick–Fuller test and choose the number of lags using the general-to-specific procedure recommended by Campbell and Perron (1991) and Ng and Perron (1995). The 1%, 5%, and 10% MacKinnon critical values vary slightly across variables because of different lags used in the tests; and they are approximately equal to −3.50, −2.89, and −2.58, respectively. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

use the short-term and long-term interest rates obtained from IFS. The excess stock market return is the difference between MSCI (Morgan Stanley Capital International) value-weighted stock market returns and the short-term interest rate obtained from IFS. Realized aggregate stock market volatility is the sum of squared daily excess MSCI value-weighted stock market returns in a quarter. As in Guo and Savickas (2007), we construct average firm-level idiosyncratic volatility using daily individual stock return data obtained from Datastream. We do not have sufficient data to construct the default premium for other G7 countries, however. For brevity, we do not report summary statistics of foreign financial variables here but they are available on request.

4. In-sample forecasts

For quarterly data, the general model of exchange rates is a single equation VAR model with four lags, and we use Krolzig and Hendry's (2001) computer automated program *PcGets* to eliminate statistically insignificant variables. Table 2 reports the regression results and diagnostic statistics of selected final models. We consider the exchange rates of the US dollar against currencies of other G7 countries, including the Canadian dollar (panel A), the French franc (panel B), the Deutsche mark (panel C), the Italian lira (panel D), the Japanese yen (panel E), and the British pound (panel F). As a robustness check, we also consider an extended sample for the Deutsche mark by using the euro/U.S. dollar rate over the period 1999:Q1–2003:Q4 (panel G). Because volatility has an approximately log-normal distribution, we use log stock market volatility (LMV) and log idiosyncratic volatility (LIV) in the regression analysis, although we find similar results by using levels. To distinguish US and foreign variables, we use LIV_US and LIV_L, for example, to denote US LIV and foreign LIV, respectively.

In each panel of Table 2, we present the OLS estimation results in the first row and the diagnostic statistics in the second row. For brevity, we do not report the constant term. The diagnostic statistics indicate that except for the British pound, we fail to reject the null hypothesis that error terms are homoskedastic and serially uncorrelated at the 10% significance level. For robustness, we use Newey-West heteroskadesticity and autocorrelation consistent standard errors (as reported in parentheses) for

Table 2
Forecasting changes in log nominal exchange rates: quarterly data

Panel A Canadian dollar (1973:Q1–2003:Q4)						
LMV_US(−2)						ARSQ
-0.009^{**}						0.061
(0.004)						
Chow test	0.114	Hetero	0.443	DW	1.932	
Panel B French Franc (1973:Q1 to 1998:Q4)						
LIV_US(−2)						ARSQ
0.054^{***}						0.066
(0.017)						
Chow test	0.446	Hetero	0.296	DW	1.806	
Panel C Deutsche mark (1973:Q1–1998:Q4)						
LIV_US(−2)						ARSQ
0.061^{***}						0.080
(0.013)						
Chow test	0.379	Hetero	0.118	DW	2.022	
Panel D Italian Lira (1973:Q1 to 1998:Q4)						
LIV_US(−2)						ARSQ
0.049^{***}						0.055
(0.014)						
Chow test	0.377	Hetero	0.257	DW	1.747	
Panel E Japanese Yen (1973:Q1 to 2003:Q4)						
RREL_US(−4)						ARSQ
4.892^{***}						0.063
(1.330)						
Chow test	0.363	Hetero	0.455	DW	1.895	
Panel F British Pound (1973:Q1 to 2003:Q4)						
ERET_US(−1)	LMV_L(−1)	RREL_L(−1)	RREL_L(−3)	RREL_L(−4)		ARSQ
0.115^{**}	0.018^{***}	-10.700^{**}	11.119^{***}	-12.540^{***}		0.136
(0.036)	(0.005)	(4.332)	(3.941)	(3.342)		
Chow test	0.878	Hetero	0.291	DW	1.584^{**}	
Panel G Deutsche Mark (1973:Q1 to 1998:Q4) and Euro (1999:Q1– 2003:Q4)						
LIV_US(−1)	LIV_L(−1)					ARSQ
0.066^{***}	-0.034^{***}					0.078
(0.016)	(0.011)					
Chow test	0.565	Hetero	0.290	DW	2.145	

Notes: The table reports the estimation results of forecasting one-quarter-ahead changes in log nominal exchange rates. We select the forecasting models using Krolzig and Hendry's (2001) computer-automated general-to-specific model selection procedures. In particular, we start with a single equation VAR model with four lags, in which the independent variables include the default premium (DEF), the term premium (TERM), the stochastically detrended risk-free rate (RREL), log stock market volatility (LMV), log idiosyncratic volatility (LIV), and lagged dependent variable (DFX). To forecast the exchange rate of U.S. dollar against a foreign country's currency, we include financial variables from both US and the foreign country in the general model. To distinguish US and foreign variables, we use LIV_US, for example, to denote US log idiosyncratic volatility and use LIV_L, for example, to denote the foreign country's idiosyncratic volatility. We then use standard testing procedures to eliminate statistically insignificant variables, with diagnostic tests checking the validity of reductions, ensuring a congruent final selection. We report the Newey-West standard errors in parentheses, and asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. "Chow test" denotes the significance level of the Chow test of the null hypothesis that there is no structural break in the middle point of the sample. "Hetero" denotes the significance level of the Breusch–Pagan test of the null hypothesis that error terms are homoskedastic. "DW" denotes the Durbin–Watson test statistic.

inference, although results are qualitatively similar using OLS standard errors.[7]

Except for the British pound, Krolzig and Hendry's (2001) general-to-specific model selection procedures result in a parsimonious final model with one or two forecasting variables. Table 2 shows that the explanatory variables included in the final models are always statistically significant at least at the 5% level, and they account for about 6% to 14% of variation in nominal exchange rates. Therefore, as conjectured, financial variables do have significant forecasting power for exchange rates.

The results reported in Table 2 exhibit some noteworthy patterns. First, US financial variables appear to be a more important determinant of the foreign price of the

[7] Note that Newey-West standard errors are consistent even if error terms are homoskedastic and serially uncorrelated.

US dollar than their foreign counterparts. At least one US variable is included in the final model of each bilateral exchange rate. By contrast, foreign variables do not help explain the Canadian dollar, the French franc, the Deutsche mark in short sample (panel C), the Italian Lira, and the Japanese yen. Second, US idiosyncratic volatility (LIV_US) appears to be a pervasive forecasting variable: It is included in the final models for the French franc, the Deutsche mark in both short sample (panel C) and extended sample (panel G), and the Italian Lira. LIV_US also forecasts the exchange rates of Japanese yen and the British pound, although it is not selected in the final models of these exchange rates. In contrast, evidence is much less consistent for the other financial variables: They forecast some exchange rates but not others. Third, we use the Chow test to investigate whether there is a structural break in the middle point of the sample and find that the forecasting models are quite stable across time. For all exchange rates, we fail to reject the null hypothesis of no structural break at the 10% significance level. This result should help explain the significant out-of-sample predictive ability of our selected models, as we discuss in Section 5. Lastly, financial variables tend to influence exchange rates with some delays. For example, the change in LIV_US affects many exchange rates after two quarters. This result helps explain that exchange rate predictability tends to increase with forecasting horizons, as we discuss next.

Many authors, e.g., Meese and Rogoff (1983) and Mark (1995), find that the predictive power of monetary fundamentals for exchange rates increases with forecasting horizons. To explore this issue, we repeat the regression analysis using semi-annual data. To convert quarterly data into semi-annual data, the dependent variable is the change in log nominal exchange rates in either the first two quarters or the last two quarters of a year, and we use observations of the second and fourth quarters for the independent variables. For example, in our general specifications of a single equation VAR model with two lags for semi-annual data, we use financial variables observed in 1990:Q2 and 1990:Q4 to forecast the change in log nominal exchange rates over the period 1991:Q1–1991:Q2. Unlike Mark (1995), we use *non-overlapping* data. This difference is important because, as stressed by Kilian (1999) and Berkowitz and Giorgianni (2001), overlapping data introduce additional complications that cannot be easily dealt with and thus make the regression results difficult to interpret.

Table 3 reports the estimation results and diagnostic statistics of the final models for semi-annual data. Exchange rate predictability indeed increases with forecasting horizons; for example, the adjusted R-squared is substantially higher for semi-annual data than for quarterly data (as reported in Table 2). Other main findings, however, are qualitatively similar to those obtained from quarterly data. In particular, we find that idiosyncratic volatility is a crucial determinant of exchange rates. US idiosyncratic volatility (LIV_US) is included in the final models for all currencies except for the Canadian dollar and the Japanese yen. Because U.S. idiosyncratic volatility closely correlates with US stock market volatility, LMV_US (see Table 1), we find qualitatively similar results by replacing LMV_US with LIV_US in the final model for the Japanese yen/US dollar rate.[8] Similarly, Japanese (panel E) and German (panel G) idiosyncratic volatilities are also an important determinant of the Japanese yen/US dollar rate and the Deutsche mark/US dollar rate, respectively. A relatively high level of a country's idiosyncratic volatility is associated with an appreciation of the country's currency.

We also conduct the regression analysis using non-overlapping annual data, for which the general model is a single equation VAR model with one lag. For example, we use observations in 1990:Q4 to forecast changes in log nominal exchange rates over the period 1991:Q1–1991:Q4. Again, we find that idiosyncratic volatility is a crucial determinant of exchange rates, as shown in Table 4. US idiosyncratic volatility is included in the final models of all foreign currencies except for the Canadian dollar. Similarly, German idiosyncratic volatility (panel G) is also an important determinant of the Deutsche mark/US dollar rate.[9] Except for Italy, a high level of a country's idiosyncratic volatility is always associated with an appreciation of the country's currency.

The main finding of a positive relation between US idiosyncratic volatility and the foreign price of the US dollar appears to be quite robust. First, it is unlikely an artifact caused by outliers. To illustrate this point, in Fig. 1 we plot log US idiosyncratic volatility against the change in the one-year-ahead log nominal Deutsche mark/US dollar rate over the period 1973–1998 and the log nominal euro/US dollar rate over the period 1999–2003. Fig. 1 shows that the strong positive relation between idiosyncratic volatility and the exchange rates is quite stable across time. Second, we find that US idiosyncratic volatility is positively correlated with future exchange rates of the US dollar against the currencies of most OECD countries in quarterly, semi-annual, and annual data. For example, Fig. 2 illustrates a strong positive relation between US idiosyncratic volatility and the change in the one-year-ahead log nominal Swiss franc/US dollar rate. For brevity, we do not report the regression results here but they are available on request. Third, as we discuss next, US idiosyncratic volatility has significant out-of-sample predictive power for exchange rates of the US dollar against major foreign currencies.

[8] For example, If we exclude LMV_US from the general model, the final model for the Japanese yen/US dollar rate selected by *PcGets* includes LIV_US(−1) as well as RREL_US(−2) and LIV_L(−2). LIV_US does not forecast the Canadian dollar/US dollar rate, however.

[9] We find qualitatively similar results if we replace Japanese stock market volatility with Japanese idiosyncratic volatility because these two variables are closely correlated to each other.

Table 3
Forecasting changes in log nominal exchange rates: semi-annual data

Panel A Canadian Dollar (1973 to 2003)						
LMV_US(−1)						ARSQ
−0.015*						0.075
(0.008)						
Chow test	0.163	Hetero	0.527	DW	1.946	
Panel B French Franc (1973 to 1998)						
LIV_US(−1)						ARSQ
0.128***						0.155
(0.0481)						
Chow test	0.781	Hetero	0.895	DW	1.792	
Panel C Deutsche Mark (1973 to 1998)						
LIV_US(−1)						ARSQ
0.143***						0.197
(0.033)						
Chow test	0.645	Hetero	0.362	DW	2.033	
Panel D Italian Lira (1973 to 1998)						
LIV_US(−1)						ARSQ
0.109***						0.110
(0.035)						
Chow test	0.474	Hetero	0.473	DW	1.763	
Panel E Japanese Yen (1973 to 2003)						
LMV_US(−1)	RREL_US(−2)	LIV_L(−2)				ARSQ
0.059***	9.504***	−0.078**				0.270
(0.016)	(3.152)	(0.032)				
Chow test	0.532	Hetero	0.518	DW	2.187	
Panel F British Pound (1973 to 2003)						
LIV_US(−1)	DEF_US(−1)					ARSQ
0.046***	0.048***					0.097
(0.016)	(0.016)					
Chow test	0.727	Hetero	0.194	DW	2.012	
Panel G Deutsche Mark (1973 to 1998) and Euro (1999 to 2003)						
LIV_US(−1)	LIV_L(−1)					ARSQ
0.170***	−0.089***					0.241
(0.028)	(0.019)					
Chow test	0.742	Hetero	0.149	DW	2.207	

Notes: The table reports the estimation results of forecasting two-quarter-ahead changes in log nominal exchange rates. We select the forecasting models using Krolzig and Hendry's (2001) computer-automated general-to-specific model selection procedures. In particular, we start with a single equation VAR model with two lags, in which the independent variables include the default premium (DEF), the term premium (TERM), the stochastically detrended risk-free rate (RREL), log stock market volatility (LMV), log idiosyncratic volatility (LIV), and lagged dependent variable (DFX). To forecast the exchange rate of US dollar against a foreign country's currency, we include financial variables from both US and the foreign country in the general model. To distinguish US and foreign variables, we use LIV_US, for example, to denote US log idiosyncratic volatility and use LIV_L, for example, to denote the foreign country's idiosyncratic volatility. We then use standard testing procedures to eliminate statistically insignificant variables, with diagnostic tests checking the validity of reductions, ensuring a congruent final selection. We report the Newey-West standard errors in parentheses, and asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. "Chow test" denotes the significance level of the Chow test of the null hypothesis that there is no structural break in the middle point of the sample. "Hetero" denotes the significance level of the Breusch–Pagan test of the null hypothesis that error terms are homoskedastic. "DW" denotes the Durbin–Watson test statistic.

5. Out-of-sample forecasts

In this Section, we compare the out-of-sample forecasting ability of the final models reported in Tables 2–4 with that of a benchmark random walk model. This exercise is important because most studies subsequent to Meese and Rogoff (1983) confirm their finding that a random walk model provides a better description of exchange rates across time than do alternative models. The empirical evidence appears to be so compelling that Engel and West (2005) argue that exchange rates might indeed follow a random walk process. Given their significant in-sample predictive power, financial variables might forecast exchange rates out of sample and thus shed new light on the time-series properties of exchange rates. Also, because we select forecasting variables based on their in-sample performance, our results could reflect data mining. Out-of-sample forecasts alleviate such a concern.

Table 4
Forecasting changes in log nominal exchange rates: annual data

Panel A Canadian Dollar (1973 to 2003)						
LMV_US(−1)						ARSQ
-0.028^{*}						0.120
(0.014)						
Chow test	0.063	Hetero	0.933	DW	1.404^{**}	
Panel B French Franc (1973 to 1998)						
LIV_US(−1)	DFX(−1)					ARSQ
0.200^{***}	0.412^{**}					0.366
(0.048)	(0.118)					
Chow test	0.915	Hetero	0.208	DW	1.682^{*}	
Panel C Deutsche Mark (1973 to 1998)						
LIV_US(−1)						ARSQ
0.209^{***}						0.292
(0.047)						
Chow test	0.862	Hetero	0.126	DW	1.332^{**}	
Panel D Italian Lira (1973 to 1998)						
LIV_US(−1)	LIV_L(−1)	LMV_L(−1)				ARSQ
0.223^{***}	0.247^{***}	-0.124^{**}				0.407
(0.053)	(0.050)	(0.047)				
Chow test	0.771	Hetero	0.357	DW	1.369^{***}	
Panel E Japanese Yen (1973 to 2003)						
LIV_US(−1)	RREL_US(−1)	LMV_L(−1)				ARSQ
0.194^{***}	15.108^{***}	-0.137^{***}				0.395
(0.044)	(5.551)	(0.043)				
Chow test	0.973	Hetero	0.202	DW	2.353	
Panel F British Pound (1973 to 2003)						
LIV_US(−1)	TERM_US(−1)					ARSQ
0.049^{**}	0.015^{***}					0.193
(0.019)	(0.005)					
Chow test	0.555	Hetero	0.981	DW	0.623^{***}	
Panel G Deutsche Mark (1973 to 1998) and Euro (1999 to 2003)						
LIV_US(−1)	LIV_L(−1)					ARSQ
0.294^{***}	-0.154^{***}					0.368
(0.047)	(0.030)					
Chow test	0.791	Hetero	0.117	DW	1.665^{*}	

Notes: The table reports the estimation results of forecasting one-year-ahead changes in log nominal exchange rates. We select the forecasting models using Krolzig and Hendry's (2001) computer-automated general-to-specific model selection procedures. In particular, we start with a single equation VAR model with one lag, in which the independent variables include the default premium (DEF), the term premium (TERM), the stochastically detrended risk-free rate (RREL), log stock market volatility (LMV), log idiosyncratic volatility (LIV), and lagged dependent variable (DFX). To forecast the exchange rate of US dollar against a foreign country's currency, we include financial variables from both US and the foreign country in the general model. To distinguish US and foreign variables, we use LIV_US, for example, to denote US log idiosyncratic volatility and use LIV_L, for example, to denote the foreign country's idiosyncratic volatility. We then use standard testing procedures to eliminate statistically insignificant variables, with diagnostic tests checking the validity of reductions, ensuring a congruent final selection. We report the Newey-West standard errors in parentheses, and asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. "Chow test" denotes the significance level of the Chow test of the null hypothesis that there is no structural break in the middle point of the sample. "Hetero" denotes the significance level of the Breusch–Pagan test of the null hypothesis that error terms are homoskedastic. "DW" denotes the Durbin–Watson test statistic.

We specify the benchmark random walk model and the alternative forecasting model in Eqs. (3) and (4), respectively:

$$\Delta s_{t+1} = c_1 + \varepsilon_{t+1} \tag{3}$$

$$\Delta s_{t+1} = c_2 + b * x_t + \zeta_{t+1}, \tag{4}$$

where x_t is a vector of selected forecasting variables (as reported in Tables 2–4), c_1 and c_2 are constants, b is a vector of coefficients, and ε_{t+1} and ζ_{t+1} are forecasting errors.

To address the small sample problem, we conduct a bootstrapping analysis similar to that in Lettau and Ludvigson (2001) and Goyal and Santa-Clara (2003). Under the null hypothesis, the data-generating process of exchange rates is assumed to be described by Eq. (3). We also assume that the forecasting variables, x_{t+1}, follow a VAR process with one lag:

$$x_{t+1} = c_3 + d * x_t + e * \Delta s_t + \eta_{t+1}, \tag{5}$$

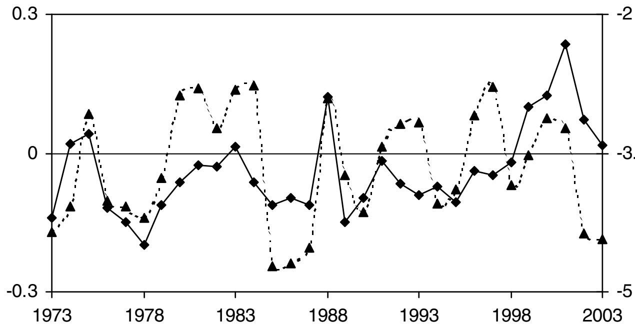

Fig. 1. Log average firm-level idiosyncratic volatility (solid line, right scale) vs. one-year-ahead changes in log nominal deutsche mark rate (1973–1998) and Euro rate (1999–2003).

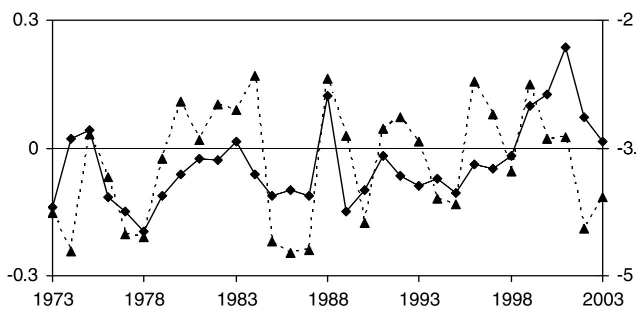

Fig. 2. Log average firm-level idiosyncratic volatility (solid line, right scale) vs. one-year-ahead changes in log nominal Swiss franc rate.

where c_3 is a vector of constants, d and e are vectors of coefficients, and η_{t+1} is a vector of error terms. In Eq. (5) we also include the lagged change in log nominal exchange rates, although excluding it does not change our results in any qualitative manner. We estimate Eqs. (3) and (5) using the full sample and save the error terms. We then generate simulated data by using the estimated coefficients and drawing the error terms with replacement. The initial values are set to the sample averages in simulations. We then use the simulated data to calculate the various statistics and repeat the process 10,000 times to obtain their empirical distributions.

As in Lettau and Ludvigson (2001), we use one third of observations for initial in-sample regression and make a one-period-ahead forecast. We then expand the sample by including one more observation and make another one-period-ahead forecast and so forth. To gauge the out-of-sample forecast performance, we use the mean-squared-error (MSE) ratio, MSE_A/MSE_B, the encompassing (ENC-NEW) test proposed by Clark and McCracken (2001), and the equal forecasting ability (MSE-F) test proposed by McCracken (1999). Clark and McCracken (2001) show that the ENC-NEW and MSE-F tests have good size and power properties in small samples. For these two tests, we obtain the 5% critical values using the bootstrapping method discussed above.

Table 5 shows that our forecasting models always outperform the benchmark random walk model in the out-of-sample forecast of exchange rates for quarterly, semi-annual, and annual data. The average of squared forecasting errors is substantially smaller for our forecasting models than for the random walk model. In most cases, the ENC-NEW and MSE-F tests indicate that the difference in out-of-sample performance is statistically significant at the 5% level.

Table 5
Out-of-sample forecasts

	MSE_A/MSE_B	ENC-NEW		MSE-F	
		Statistic	BS CV	Statistic	BS CV
Panel A quarterly data					
Canada	0.938	4.658	2.268	5.314	1.679
France	0.922	4.270	2.275	5.649	1.551
Germany (1973–1998)	0.922	4.765	2.280	5.698	1.475
Italy	0.941	3.405	2.352	4.200	1.450
Japan	0.944	3.569	2.128	4.694	1.457
U.K.	0.911	11.188	4.489	7.757	0.050
Germany (1973–2003)	0.920	10.053	3.250	7.072	1.292
Panel B semi-annual data					
Canada	0.936	3.049	2.300	2.730	1.479
France	0.796	6.199	2.423	8.704	1.526
Germany (1973–1998)	0.771	7.474	2.377	10.117	1.538
Italy	0.861	3.922	2.453	5.473	1.608
Japan	0.753	10.976	3.758	12.806	1.226
U.K.	0.976	3.215	3.451	0.978	1.257
Germany (1973–2003)	0.809	13.221	3.356	9.433	1.452
Panel C annual data					
Canada	0.958	1.658	2.159	0.886	1.431
France	0.663	8.199	3.347	8.119	1.741
Germany (1973–1998)	0.708	6.695	2.565	6.597	1.871
Italy	0.680	10.354	4.195	7.519	1.410
Japan	0.745	10.904	4.064	6.853	0.925
U.K.	0.899	6.112	3.655	2.257	0.978
Germany (1973–2003)	0.772	9.906	3.700	5.898	1.679

Notes: The table reports out-of-sample forecasts for changes in log nominal exchange rates. We use first one third observations for initial in-sample regression and make a one-period-ahead forecast. We then expand the sample by one observation and make another forecast and so forth. MSE_A/MSE_B is the ratio of mean squared-error of the forecasting model (as reported in Tables 2–4) to that of a benchmark random walk model. ENC-NEW is the encompassing test proposed by Clark and McCracken (2001) and MSE-F is the equal forecasting ability test by McCracken (1999). BS CV is the bootstrapping 5% critical value; see Section 5 for more details.

Tables 2–4 show that US idiosyncratic volatility is a crucial determinant of the US dollar rate. In an earlier version of this paper, we show that US idiosyncratic volatility by itself has significant out-of-sample forecasting power for the exchange rates of the US dollar against major foreign currencies, even after we explicitly control for data miming using a procedure proposed by Rapach and Wohar (2006). For brevity, we do not report these results here but they are available on request. To summarize, in contrast with earlier studies, our empirical evidence indicates that exchange rates are predictable out-of-sample.

6. Discussion and conclusion

This paper shows that financial variables forecast exchange rates of the US dollar against major foreign currencies in and out-of-sample. In particular, we document a strong positive relation between a country's idiosyncratic volatility and future prices of the country's currency in terms of a foreign currency. Our evidence suggests that, in contrast with most of existing empirical results, foreign exchange rates are predictable.

Idiosyncratic volatility forecasts exchange rates possibly because of its influence on monetary fundamentals. Lilien (1982) argues that an increase in idiosyncratic volatility induces resource reallocation across firms or industries and thus temporarily reduces employment and output. Consistent with this hypothesis, Loungani et al. (1990), CLMX, and Comin and Philippon (2005) find in US data that idiosyncratic volatility correlates negatively with future aggregate employment and output. In an earlier version of this paper, we show that US idiosyncratic volatility also helps forecast GDP growth in other G7 countries.

There are two possible explanations for why financial variables perform better in forecasting exchange rates than do monetary fundamentals. First, financial variables provide a good measure of broad business conditions and thus are potentially less vulnerable to the omitted variables problem (e.g., Meese, 1990). Second, fundamentals such as output and monetary aggregates are subject to data revisions, which can obscure the forecasting relation stipulated by monetary models (e.g., Faust et al., 2003). In contrast, the financial variables used in this paper are available to investors at the time of forecast.

The positive relation between US idiosyncratic volatility and future US dollar rate possibly reflects the fact that, as reported in an earlier version of this paper, the adverse effect of US idiosyncratic volatility on aggregate output is stronger for foreign countries than for US. It is unclear, however, why German and Japanese idiosyncratic volatilities correlate positively with the US dollar price of the Deutsche mark and the Japanese yen, respectively.

Alternatively, Guo and Savickas (2007) find that when combined with stock market volatility, idiosyncratic volatility forecasts excess stock market returns in G7 countries. Because stocks, bonds, and foreign exchanges are susceptible to the same macroeconomic risk, the expected risk premia that investors require for holding these assets might closely relate to each other. Therefore, idiosyncratic volatility could be a proxy for conditional foreign exchange risk premia. In particular, Guo and Savickas argue that idiosyncratic volatility could be a measure of investment opportunities. When a new technology is discovered, it creates opportunities for some firms, but not for others. Thus, the relation between idiosyncratic volatility and exchange rates might reflect the fact that, ceteris paribus, a country's currency tends to appreciate after a positive shock to that country's investment opportunities.

References

Almeida, A., Goodhart, C., Payne, R., 1998. The Effects of macroeconomic news on high frequency exchange rate behavior. Journal of Financial and Quantitative Analysis 33, 383–408.

Andersen, T., Bollerslev, T., Diebold, F., Vega, C., 2004. Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets. Unpublished Working Paper.

Barro, R., 1990. The stock market and investment. Review of Financial Studies 3, 115–131.

Berkowitz, J., Giorgianni, L., 2001. Long-horizon exchange rate predictability? Review of Economics and Statistics 83, 81–91.

Bernanke, B., Blinder, A., 1992. The federal funds rate and the channels of monetary transmission. American Economic Review 82, 901–921.

Bilson, J., 1978. Rational Expectations and the Exchange Rate. In: Frenkel, Jacob A., Johnson, Harry G. (Eds.), The Economics of Exchange Rates: Selected Studies. Addison-Wesley, Reading, MA, pp. 75–96.

Boudoukh, J., Richardson, M., Whitelaw, R., 2005. The information in long-maturity forward rates: Implications for exchange rates and the forward premium anomaly. Unpublished Working Paper, NYU.

Campbell, J., 1987. Stock returns and the term structure. Journal of Financial Economics 18, 373–399.

Campbell, J., Perron, P., 1991. Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots. In: Blanchard, O., Fischer, S. (Eds.), NBER Macroeconomics Annual. MIT Press, Cambridge, pp. 141–201.

Campbell, J., Lo, A., MacKinlay, C., 1997. The Econometrics of Financial Markets. Princeton University Press, Princeton, NJ.

Campbell, J., Lettau, M., Malkiel, B., Xu, Y., 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. Journal of Finance 56, 1–43.

Clarida, R., Taylor, M., 1997. The term structure of forward exchange premiums and the forecastability of spot exchange rates: Correcting the errors. Review of Economics and Statistics 79, 353–361.

Clark, T., McCracken, M., 2001. Tests of equal forecast accuracy and encompassing for nested models. Journal of Econometrics 105, 85–110.

Comin, D., Philippon, T., 2005. The rise in firm-level volatility: Causes and consequences. In: Gertler, M., Rogoff, K. (Eds.), NBER Macroeconomics Annual, 20.

Dornbusch, R., 1976. Expectations and exchange rate dynamics. Journal of Political Economy 84, 1161–1176.

Engel, C., West, K., 2005. Exchange rates and fundamentals. Journal of Political Economy 113, 485–517.

Evans, M., Lyons, R., 2005a. Meese-Rogoff redux: Micro-based exchange rate forecasting. In: American Economic Review Papers and and Proceedings, forthcoming.

Evans, M., Lyons, R., 2005b. Exchange Rates Fundamentals and Order Flow. Unpublished Working Paper, Georgetown University.

Fama, E., French, K., 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25, 23–49.

Faust, J., Rogers, J., Wright, J., 2003. Exchange rate forecasting: The errors we've really made. Journal of International Economics 60, 35–59.

Ferson, W., Sarkissian, S., Simin, T., 2003. Spurious regressions in financial economics? Journal of Finance 58, 1393–1414.

Frenkel, J., 1976. A monetary approach to the exchange rate: Doctrinal aspects and empirical evidence. Scandinavian Journal of Economics 78, 200–224.

Goodhart, C., Hall, S., Henry, S., Pesaran, B., 1993. News effects in a high-frequency model of the sterling-dollar exchange rate. Journal of Applied Econometrics 8, 1–13.

Goyal, A., Santa-Clara, P., 2003. Idiosyncratic risk matters! Journal of Finance 58, 975–1007.

Guo, H., Savickas, R. 2007. Average Idiosyncratic Volatility in G7 Countries. Review of Financial Studies, forthcoming.

Guo, H., Whitelaw, R., 2006. Uncovering the risk-return relation in the stock market. Journal of Finance 61, 1433–1463.

Hong, Y., Lee, T., 2003. Inference on predictability of foreign exchange rates via generalized spectrum and nonlinear time series models. Review of Economics and Statistics 85, 1048–1062.

Kilian, L., 1999. Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions? Journal of Applied Econometrics 14, 491–510.

Krolzig, M., Hendry, D., 2001. Computer automation of general-to-specific model selection procedures. Journal of Economic Dynamics and Control 25, 831–866.

Lettau, M., Ludvigson, S., 2001. Consumption, aggregate, wealth and expected stock returns. Journal of Finance 56, 815–849.

Lettau, M., Ludvigson, S., 2002. Time-varying risk-premia and the cost of capital: An alternative implication of the Q theory of investment. Journal of Monetary Economics 49, 31–66.

Lilien, D., 1982. Sectoral shifts and cyclical unemployment. Journal of Political Economy 90, 777–793.

Loungani, P., Rush, M., Tave, W., 1990. Stock market dispersion and unemployment. Journal of Monetary Economics 25, 367–388.

Mark, N., 1995. Exchange rates and fundamentals: Evidence on long-horizon predictability. American Economic Review 85, 201–218.

McCracken, M., 1999. Asymptotics for out-of-sample tests of causality. Unpublished Working Paper, Louisiana State University.

Meese, R., 1990. Currency fluctuations in the Post-Bretton woods era. Journal of Economic Perspective, 117–134.

Meese, R., Rogoff, K., 1983. Empirical exchange rate models of the 1970's: Do they fit out of sample? Journal of International Economics 14, 3–24.

Merton, R., 1980. On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics 8, 323–361.

Mussa, M., 1976. The exchange rate, the balance of payments, and monetary and fiscal policy under a regime of controlled floating. Scandinavian Journal of Economics 78, 229–248.

Ng, S., Perron, P., 1995. Unit root tests in ARMA models with data dependent methods for the selection of the Truncation lag. Journal of the American Statistical Association 90, 268–281.

Rapach, D., Wohar, M., 2006. In-sample vs. out-of-sample tests of stock return predictability in the context of data mining. Journal of Empirical Finance 13, 231–247.

Stock, J., Watson, M., 2003. Forecasting output and inflation: The role of asset prices. Journal of Economic Literature 41, 788–829.

Sweeney, R., 2006. Mean reversion in G-10 nominal exchange rates, Journal of Financial and Quantitative Analysis. forthcoming.