Idiosyncratic Volatility, Economic Fundamentals, and Foreign Exchange Rates

Authors	Hui Guo, and Robert Savickas
Working Paper Number	2005-025B
Revision Date	May 2006
Citable Link	https://doi.org/10.20955/wp.2005.025
Suggested Citation	Guo, H., Savickas, R., 2006; Idiosyncratic Volatility, Economic Fundamentals, and Foreign Exchange Rates, Federal Reserve Bank of St. Louis Working Paper 2005-025. URL https://doi.org/10.20955/wp.2005.025

Idiosyncratic Volatility, Economic Fundamentals, and Foreign Exchange Rates

Hui Guo[a] and Robert Savickas[b*]

April 15, 2006

Abstract

This paper shows that a relatively high level of average U.S. industry- or firm-level idiosyncratic stock volatility is usually associated with a future appreciation in the U.S. dollar. For most foreign currencies, the relation is statistically significant in both in-sample and out-of-sample tests, even after we use a bootstrap procedure to explicitly account for data mining. We also document a positive and significant relation between a country's idiosyncratic volatility and the future U.S. dollar price of its currency—in France, Germany, and Japan. Moreover, among a number of commonly used financial variables, only idiosyncratic volatility forecasts output growth in both U.S. and foreign countries. Our results suggest that there might be a close link between exchange rates and economic fundamentals.

Keywords: exchange rate predictability, average idiosyncratic volatility, monetary model, bootstrap, and data mining.
JEL subject numbers: F31, G1.

* [a] Corresponding author: Research Division, Federal Reserve Bank of St. Louis (P.O. Box 442 St. Louis, MO, 63166, E-mail: hui.guo@stls.frb.org); and [b] Department of Finance, George Washington University (2023 G Street, N.W. Washington, DC 20052, E-mail: Savickas@gwu.edu). This paper formerly circulated under the title "Foreign Exchange Rates Don't Follow a Random Walk." We thank Mike Dueker, Chris Neely, Mark Wohar, and seminar participants at George Washington University, the World Bank, the 2005 Financial Management Association meeting, and 2006 Missouri Economic Conference for helpful comments. The views expressed in this paper are those of the authors and do not necessarily reflect the official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

Idiosyncratic Volatility, Economic Fundamentals, and Foreign Exchange Rates

Abstract

This paper shows that a relatively high level of average U.S. industry- or firm-level idiosyncratic stock volatility is usually associated with a future appreciation in the U.S. dollar. For most foreign currencies, the relation is statistically significant in both in-sample and out-of-sample tests, even after we use a bootstrap procedure to explicitly account for data mining. We also document a positive and significant relation between a country's idiosyncratic volatility and the future U.S. dollar price of its currency—in France, Germany, and Japan. Moreover, among a number of commonly used financial variables, only idiosyncratic volatility forecasts output growth in both U.S. and foreign countries. Our results suggest that there might be a close link between exchange rates and economic fundamentals.

Keywords: exchange rate predictability, average idiosyncratic volatility, monetary model, bootstrap, and data mining.
JEL subject numbers: F31, G1.

I. Introduction

Although they remain a dominant paradigm of floating exchange rates in the post-Bretton Woods era, monetary models advanced by Bilson (1978), Dornbusch (1976), Frenkel (1976), and Mussa (1976), among others, fail to provide a satisfactory explanation of the data. In an influential paper, Meese and Rogoff (1983) show that fundamentals dictated by monetary models do not outperform a naïve random walk model in the out-of-sample forecast of nominal exchange rates. Mark (1995) argues that monetary fundamentals could have some successes in explaining the exchange rate behavior by using more powerful statistical tests; however, many other authors, e.g., Kilian (1999), Berkowitz and Giorgianni (2001), and Faust, Rogers, and Wright (2003), remain skeptical. The Meese and Rogoff results appear to be strikingly robust after twenty years of fresh data and intensive academic research. With a few exceptions, e.g., Clarida and Taylor (1997), Hong and Lee (2003), Boudoukh, Richardson, and Whitelaw (2005), and Sweeney (2006), most authors find it difficult to beat the random walk model of exchange rates: Engel and West (2004), for example, argue that exchange rates might follow a random walk process.

In this paper, we investigate whether financial variables—which are predictors of monetary fundamentals—forecast exchange rates. This approach is motivated by Obstfeld and Rogoff (1996), which argues that *"the nominal exchange rate must be viewed as an asset price*. Like other assets, the exchange rate depends on expectations of future variables." (pp. 529) Our specification has two important advantages over that commonly used by early authors, e.g., Meese and Rogoff (1983), although both can reflect the same economic intuition. First, these 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, Rogers, and Wright [2003]); in contrast, most forecasting variables used in this paper are available to investors in real time.[1] Thus, our analysis may shed light on empirical evidence of exchange rate predictability.

Our forecasting specification is plausible because it is also consistent with alternative hypotheses. In particular, as we will explain in footnote 2 below, many of financial variables capture a significant portion of cyclical variations of the equity and bond premia; therefore, they might also capture cyclical variations in exchange rates because exchange rates and stock and bond prices are influenced by the same macroeconomic news (e.g., Andersen, Bollerslev, Diebold, and Vega [2004]). However, in this paper, we mainly focus on exchange rate predictability and do not attempt to formally distinguish alternative hypotheses.

We focus on the financial variables that have been found to move closely with business cycles. Fama and French (1989) use the price-dividend ratio, the default premium, and the term premium as measures of business conditions. Barro (1990) documents a strong relation between stock market returns and future business investments. Recently, Campbell, Lettau, Malkeil, and Xu (2001; hereafter CLMX) show that aggregate stock market volatility and a measure of average industry- or firm-level idiosyncratic stock volatility forecast GDP growth; Lettau and Ludvigson (2002) find that the consumption-wealth ratio is a strong predictor of business investments. We also include the stochastically detrended risk-free rate advocated by Campbell,

[1] The only exception is the consumption-wealth ratio—the error term from the cointegration relation among consumption, wealth, and labor income, which Lettau and Ludvigson (2001) estimate using the full sample. However, excluding it does not affect our results in any qualitative manner because the consumption-wealth ratio has negligible forecasting power for exchange rates.

Lo, and MacKinlay (1997), among others. See Stock and Watson (2003) for a recent comprehensive survey on the predictive power of these variables for output and inflation.[2]

In contrast with most early authors, we document strong evidence against the random walk hypothesis of nominal exchange rates. In particular, average U.S. industry- or firm-level idiosyncratic volatility is found to be a strong predictor of the U.S. dollar rate against most foreign currencies, especially over relatively long horizons. To illustrate the main result, in Figure 1 we plot log firm-level idiosyncratic volatility against the change in the nominal Deutsche mark/U.S. dollar rate one-year forward using a non-overlapping sample over the period 1973-98 and the nominal euro/U.S. dollar rate for the period 1999-2003.[3] Figure 1 reveals a strong positive relation: A high level of idiosyncratic volatility is usually associated with a future appreciation in the U.S. dollar.

Consistent with the casual observation from Figure 1, the regression analysis indicates that idiosyncratic volatility accounts for over 30% of the variation of the subsequent change in the Deutsche mark rate in non-overlapping annual data, with a t-statistic of about 5. Similarly, it accounts for over 20% (6%) of the variation of the Deutsche mark rate in non-overlapping semi-annual (quarterly) data, with a t-statistic of above 4 (3). The relation is also remarkably stable across time: We find essentially the same results in two half-samples. Therefore, it is not surprising that idiosyncratic volatility performs substantially better than the random walk benchmark in the out-of-sample forecast and the difference is statistically significant. We also

[2]Early authors find that many of these variables forecast stock and bond returns as well. A partial list includes Fama and French (1989) for the dividend yield, the default premium, and the term premium; French, Stambaugh, and Schwert (1987) and Guo and Whitelaw (2005) for stock market volatility; Lettau and Ludvigson (2001) for the consumption-wealth ratio; Campbell, Lo, and MacKinlay (1997) for the stochastically detrended risk-free rate; and Goyal and Santa-Clara (2003) for the equal-weighted average firm-level idiosyncratic volatility.

[3] We find essentially the same results using industry-level idiosyncratic volatility, which is closely correlated with firm-level idiosyncratic volatility: Their correlation coefficient is above 90%.

find very similar results for most other foreign currencies; for example, Figure 2 illustrates a strong positive relation between idiosyncratic volatility and the Swiss franc/U.S. dollar rate.

To address the potential concern for data mining, we conduct three robustness checks and find that data mining cannot fully account for our main finding. First, we adopt the bootstrap procedure proposed by Rapach and Wohar (2006), and find that exchange rate predictability remains statistically significant after explicitly accounting for data mining. Second, consistent with U.S. data, we also document a positive relation between a nation's idiosyncratic volatility and the future U.S. dollar price of its currency for most other G7 countries; the relation is statistically significant for Germany, France, and Japan. Third, we can trace the strong forecasting power of idiosyncratic volatility to its important influence on real economic activity in both the U.S. and foreign countries.

The third point above suggests that our results are potentially consistent with monetary models of exchange rates. In particular, 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 Lilien's conjecture and the empirical finding by Loungani, Rush, and Tave (1990), CLMX, and Comin and Philippon (2005), our results indicate that U.S. idiosyncratic volatility has a significantly negative effect on future U.S. GDP growth; it even drives out the lagged dependent variable from the regression at the one-year horizon. U.S. industry- or firm-level idiosyncratic volatility has significant forecasting power for foreign GDP growth as well, which is another important determinant of exchange rates in monetary models. More importantly, the negative effect of U.S. idiosyncratic volatility on output is stronger for foreign countries, e.g., Germany and Japan, than the U.S. The latter result corroborates the positive relation between U.S. idiosyncratic volatility and exchange rates of the U.S. dollar. By contrast, among the other financial variables, only the term premium provides information about future U.S. output beyond idiosyncratic volatility; nevertheless, it doesn't forecast output in foreign countries. Interestingly, as expected, except for the default premium, the other financial variables provide negligible information about future exchange rates beyond idiosyncratic volatility. The default premium has some forecasting power for exchange rates possibly because of its close relation with growth of aggregate monetary in both U.S. and some foreign countries.

Our paper is closely related to the concurrent works by Evans and Lyons (2005a, 2005b), which show that order flow forecasts exchange rates because it contains information about future fundamentals. However, Evans and Lyons use a relatively short sample spanning the period 1993 to 1999, in contrast with quarterly data covering the full post-Bretton Woods era in this paper. Engel and Hamilton (1990) and Kaminsky (1993) document long swings in the U.S. dollar over the period 1973 to 1988. We provide an interesting explanation for these results: Figures 1 and 2 show that idiosyncratic volatility, which forecasts fundamentals, tracks long swings in exchange rates remarkably well. Clarida and Taylor (1997) and Boudoukh, Richardson, and Whitelaw (2005) find that interest rate differentials forecast exchange rates out of sample; and Hong and Lee (2003) and Sweeney (2006) advocate using nonlinear time series models and panel data, respectively. We complement their results by uncovering a closer link between exchange rates and economic fundamentals. Lastly, our results are consistent with Goodhart, Hall, Henry, Pesaran (1993), Almeida, Goodhart, and Payne (1998), and Andersen, Bollerslev, Diebold, and Vega (2003), among others, who document a significant effect of macroeconomic news on exchange rates using intra-day data; also, Engel and West (2004) find that exchange rates forecast fundamentals.

The remainder of the paper is organized as follows. In Section II we derive a link between nominal exchange rates and financial variables that forecast fundamentals in both the U.S. and foreign countries. We discuss the data in Section III and investigate the relation between financial variables and fundamentals in Section IV. We present the in-sample regression results of exchange rates in Section V and conduct a number of robustness tests in Section VI. We offer some concluding remarks in Section VII.

II. The Theoretical Motivation

This section shows that, in monetary models, a financial variable forecasts exchange rates if it contains information about future fundamentals in both U.S. and foreign countries. To illustrate this point, we follow many early authors, e.g., Obstfeld and Rogoff (1996), Engel and West (2004), and Evans and Lyons (2005a), and write the nominal exchange rate as the sum of the expected discounted future fundamentals:

(1) $$S_t = (1-b)\sum_{i=0}^{\infty} b^i E_t(f_{t+i} - f_{t+i}^*),$$

where S_t is the nominal price of the U.S. dollar in foreign currencies, f_{t+i} is U.S. fundamentals, f_{t+i}^* is foreign fundamentals, and b is a discount factor, which is close to, but less than 1.

Stock and Watson (2003), among others, show that many financial variables forecast fundamentals such as GDP growth and inflation. For illustration, we assume that some financial variable, x_t, forecasts the change in U.S. fundamentals:

(2) $$f_{t+1} = f_t + \gamma x_t + \varepsilon_{t+1},$$

where γ is a slope parameter and ε_{t+1} is a forecasting error.[4] Similarly, x_t also forecasts the change in foreign fundamentals:

(3) $$f^*_{t+1} = f^*_t + \gamma^* x_t + \varepsilon^*{}_{t+1},$$

where γ^* is a slope parameter and ε^*_{t+1} is a forecasting error. For simplicity, we assume that x_t follows an AR(1) process:

(4) $$x_{t+1} = \beta x_t + \eta_{t+1},$$

where β is a slope parameter and η_{t+1} is a forecasting error.

We show in Appendix A:

(5) $$(1-b)\sum_{i=0}^{\infty} b^i E_t(f_{t+i}) = f_t + \frac{b\gamma}{1-b\beta} x_t$$

(6) $$(1-b)\sum_{i=0}^{\infty} b^i E_t(f^*_{t+1}) = f^*_t + \frac{b\gamma^*}{1-b\beta} x_t .$$

Substituting equations (5) and (6) into equation (1), we obtain

(7) $$S_t = f_t - f^*_t + \frac{b(\gamma - \gamma^*)}{1-b\beta} x_t$$

and, similarly,

(8) $$S_{t+1} = f_{t+1} - f^*_{t+1} + \frac{b(\gamma - \gamma^*)}{1-b\beta} x_{t+1} .$$

Subtracting equation (7) from equation (8), we obtain

(9) $$\Delta S_{t+1} = S_{t+1} - S_t = (f_{t+1} - f_t) - (f^*_{t+1} - f^*_t) + \frac{b(\gamma - \gamma^*)}{1-b\beta}(x_{t+1} - x_t) .$$

Substituting equations (2), (3), and (4) into equation (9), we obtain

[4] As in Engel and West (2004), among many others, we implicitly assume that fundamentals are first-difference stationary. Also, it is straightforward to extend to the case in which x_t is a vector of financial variables.

(10) $$\Delta S_{t+1} = \frac{(1-b)(\gamma-\gamma^*)}{1-b\beta} x_t + \xi_{t+1},$$

where $\xi_{t+1} = (\varepsilon_{t+1} - \varepsilon^*_{t+1}) + \frac{b(\gamma-\gamma^*)}{1-b\beta}\eta_{t+1}$ is a shock to the exchange rate.

Equation (10) is the main empirical specification analyzed in this paper. It indicates that a financial variable forecasts the change in nominal exchange rates because of its influence on future U.S. and foreign fundamentals. However, while we use equation (10) to motivate our empirical analysis, it does not provide a formal test for monetary models. In particular, equation (10) is also consistent with the alternative hypothesis that foreign exchange rates have a cyclical risk premium because business cycles are one of the most important risks in foreign exchange markets (e.g., Andersen, Bollerslev, Diebold, and Vega [2003]). In this paper, we focus mainly on exchange rate predictability and do not attempt to formally distinguish the two hypotheses.

III. Data

We obtain quarterly nominal exchange rate data from IFS (International Financial Statistics).[5] Exchange rates are all denoted as the prices of the U.S. dollar in foreign currencies, e.g., the Deutsche mark/U.S. dollar rate. With the introduction of the euro in 1999, data for euro area countries are only available until 1998. We focus mainly on the sample period 1973:Q1 to 1998:Q4, over which we have data for all countries. To be robust, we also analyze the full sample period 1973:Q1 to 2004:Q2 for non-euro area countries. Following the early literature,

[5] As in Mark (1995) and many others, we use quarterly data because fundamentals such as GDP growth are available only at the quarterly frequency. To be robust, we have also investigated monthly data and find qualitatively similar but somewhat weaker results for at least two reasons. First, Ghysels, Santa-Clara, and Valkanov (2005) argue that realized volatility is a function of long distributed lags of past daily returns. Therefore, average industry- and firm-level idiosyncratic volatility, which are important predictors of exchange rates, are likely to be more

e.g., Meese and Rogoff (1983), we investigate the predictability of *nominal* exchange rates. In particular, as stipulated in equation (10), we use financial variables to forecast their changes—the log difference between the nominal exchange rates at the end and beginning of a period. Meese and Rogoff (1983) and Mark (1995), among others, show that exchange rate predictability varies with forecasting horizons. To address this issue, we analyze non-overlapping data for three different horizons—quarterly, semi-annual, and annual.

Panel A of Table 1 provides summary statistics of quarterly changes in exchange rates for six G7 countries and Switzerland over the period 1973:Q1 to 1998:Q4. Exchange rates exhibit a substantial trend for some currencies. For example, the Japanese yen and the Swiss franc have appreciated over 10% per year, while the Italian lira has depreciated over 12% per year. Except for the Canadian dollar, exchange rates are quite volatile, with the quarterly standard deviation around 6%. The autocorrelation is usually moderate. The Canadian dollar rate is essentially uncorrelated with the other exchange rates; however, the other exchange rates are strongly correlated among themselves, with an average correlation coefficient about 0.69. To conserve space, we do not report the summary statistics for semi-annual and annual data, which are very similar to those for quarterly data.

Unless otherwise indicated, we use predictive variables from U.S. data. This is because, except for idiosyncratic volatility, their foreign counterparts—if available to us—have negligible forecasting power for exchange rates. One possible explanation is that the strong co-movements of exchange rates (panel A, Table 1) indicate that they are likely to be influenced by the same U.S. macroeconomic forces. Nevertheless, we find that foreign idiosyncratic volatility does provide some information about future exchange rates beyond U.S. idiosyncratic volatility.

---

precisely estimated at the quarterly frequency than the monthly frequency. Second, in this paper, we find that the exchange rate predictability tends to increase with forecasting horizons.

We obtained the consumption-wealth ratio (CAY) from Martin Lettau at New York University. We obtained the dividend yield (DP) on the S&P 500 Index from Standard and Poor's. The default premium (DEF) is the difference between yields on Baa- and Aaa-rated corporate bonds obtained also from Standard and Poor's. The term premium (TERM) is the difference between yields on 10-year Treasury bonds and 3-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.

As in Merton (1980), among many others, we define realized aggregate stock market volatility (MV) as the sum of squared daily excess CRSP value-weighted stock market returns in a quarter. We use the same value-weighted average industry-level idiosyncratic volatility (IND) as in CLMX, which we obtained from Martin Lettau for the period 1962:Q3 to 1997:Q4 and updated through 2003:Q4. Lastly, our measure of average firm-level idiosyncratic volatility (FIRM) is slightly different from that in CLMX: They assume that the loading on stock market risk is equal to unity for all stocks, although it exhibits substantial cross-sectional variations in the data. To provide a better proxy for the cross-sectional dispersion in Lilien (1982), we estimate the loading on stock market risk directly using a rolling window. See Appendix B for details about the construction of average firm-level idiosyncratic volatility in both the U.S. and the other G7 countries. Our firm-level idiosyncratic volatility measure has similar but noticeably better predictive power for GDP growth as well as exchange rates than that constructed by

CLMX; interestingly, as shown below, it is closely correlated with and has forecasting power very similar to the CLMX industry-level idiosyncratic volatility measure.

Panel B of Table 1 provides summary statistics for the forecasting variables over the period 1973:Q1 to 1998:Q4; we find very similar results using the full sample 1973:Q1 to 2003:Q4, which are available on request. Ferson, Sarkissian, and Simin (2003), among others, show that persistent predictive variables might lead to spurious regressions, especially in the context of data mining. However, except for DP, our forecasting variables are not very persistent, with an autocorrelation coefficient equal to or less than 0.9, which is considerably lower than that of the variables considered in Ferson et al.

IV. GDP Growth Regressions

Section II shows that, in monetary models, predictive variables of exchange rates should also forecast economic fundamentals in both the U.S. and foreign countries. This point is especially relevant for our empirical analysis because it alleviates the concern for data mining. In Table 2 we present the OLS estimation results of regressing U.S. real GDP growth on various predetermined variables using quarterly, semi-annual, and annual data over the period 1963:Q1 to 2003:Q4, the longest sample over which we have data for all variables.[6] Throughout the paper, we use the observations from the most recent quarter for the independent variables in the regression for semi-annual and annual data.

Our results are consistent with the early authors, e.g., Stock and Watson (2003) and CLMX. In particular Table 2 shows that the term premium, TERM, the excess stock market return, ERET, industry-level idiosyncratic volatility, IND, and firm-level idiosyncratic volatility, FIRM, are statistically significant at all horizons. Aggregate stock market volatility, MV, is also statistically significant at quarterly and semi-annual frequencies. Volatility might have a log-normal distribution. To be robust, we also use a log-transformation for aggregate stock market volatility (LMV), firm-level idiosyncratic volatility (LFIRM), and industry-level idiosyncratic volatility (LIND) and find that they have very similar or slightly better explanatory power than levels. In contrast, the default premium, DEF, the dividend yield, DP, the stochastically detrended risk-free rate, RREL, and consumption-wealth ratio, CAY, provide negligible information about future output.

We also confirm the result by CLMX that industry- and firm-level volatilities have very similar explanatory power for GDP growth. In particular, although individually significant in Table 2, they become statistically insignificant when both variables are included as the independent variables in the regression. This result should not be a surprise because they are closely correlated with each other (Table 1). Interestingly, both volatility measures subsume the information content of the other variables except TERM, especially at the one-year horizon. Also, adding TERM to the forecasting equation has little effect on the predictive power of industry- or firm-level idiosyncratic volatility: They appear to capture different variations in output possibly because they are proxies of different shocks to the U.S. economy. For example, while the term premium reflects the stance of monetary policy (e.g., Bernanke and Blinder [1992]), industry- or firm-level idiosyncratic shocks induce costly resource reallocation across industries or firms (e.g., Lilien [1982]). To conserve space, these results are not reported here but are available on request.

---

[6] Stock and Watson (2003) find that exchange rates have some out-of-sample predictive power for output; however, consistent with Engel and West (2004), we fail to uncover it using the OLS regression possibly because the relation

Equation (10) shows that foreign fundamentals should play an equally important role in the determination of exchange rates as U.S. fundamentals. Therefore, a financial variable forecasts exchanges rates because it also forecasts foreign fundamentals. To address this issue, we investigate whether U.S. financial variables forecast GDP growth in G7 countries over the period 1963:Q1 to 1999:Q4 and report the results in Table 3.[7] We only report the results for TERM, ERET, LMV, LFIRM, and LIND: MV, FIRM, and IND have forecasting power very similar to their log transformations; and the other variables have negligible forecasting power, as in U.S. data. For brevity, we focus on the quarterly frequency because the results are essentially the same for semi-annual and annual frequencies.

Table 3 shows that LFIRM and LIND are strong predictors of GDP growth in most foreign countries and LMV is also significant in Germany, Japan, and the U.K.[8] By contrast, the predictive power of TERM—a proxy for the stance of U.S. monetary policy—is negligible in most cases possibly because central banks in foreign countries have maintained independent monetary policy since the collapse of the Bretton Woods system. Also, ERET is insignificant for all foreign countries. Therefore, these international results confirm U.S. evidence that idiosyncratic volatility appears to have a strong relation with fundamentals.

Lastly, we find that DEF, TERM, RREL, and DP forecast the growth rate of the U.S. nominal monetary aggregates (M1), another important fundamental in monetary models. However, they do not exhibit consistent forecasting power for M1 in the other G7 countries. To conserve space, these results are not reported here but are available on request.

---

between exchange rates and fundamentals is nonlinear, as argued by Kilian and Taylor (2003).

[7] When this paper was first written, the GDP data for most G7 countries were under substantial revisions and were available for a very short sample period. Instead, we use the real GDP data in Stock and Watson (2003), which were obtained from Mark Watson at Princeton University.

[8] Again, we find that LMV forecasts real GDP growth in foreign countries because of its co-movements with LFIRM and LIND.

To summarize, we find that U.S. industry- or firm-level idiosyncratic volatility is a strong predictor of fundamentals in both the U.S. and foreign countries. According to monetary models or the time-varying risk premium hypothesis, these variables are likely to forecast the change in nominal exchange rates. As we show below, this conjecture is strongly supported by the data.

V. In-Sample Regressions of U.S. Dollar Rates against Major Foreign Currencies

A. A Single Explanatory Variable

Table 4 reports the OLS estimation results of regressing one-quarter-ahead changes in nominal exchange rates on various financial variables over the period 1973:Q1 to 1998:Q4, with a total of 104 observations. A constant term is also included in the regression but, for brevity, it is not reported here. We focus on seven major currencies, namely, Canadian dollars, French francs, German marks, Italian liras, Japanese yens, Swiss francs, and British pounds. We calculate t-values using White-corrected standard errors; using the Newey-West correction generates essentially the same results. As shown in Table 1, many nominal exchange rates exhibit a trend in our sample period; however, we find no trend for the change in nominal exchange rates—the dependent variable in the regression. Also, CLMX and Comin and Philippon (2005), among others, document an upward trend in U.S. firm-level idiosyncratic volatility, especially for small stocks. To address this issue, we use the value-weighted measure; also, we experiment with adding a linear time trend to the regression and find essentially the same results, which are available on request.

In Table 4, firm-level idiosyncratic volatility, FIRM, stands out as a consistent predictor of the change in nominal exchange rates. It is statistically significant for France, Germany, Italy, and Switzerland and marginally significant for the U.K. Interestingly, except for Canada, its coefficient is positive for all countries, indicating that a relatively high level of idiosyncratic volatility is usually associated with a future appreciation in the U.S. dollar. We find essentially the same results using industry-level idiosyncratic volatility, IND, which is closely correlated with, (Table 1) and has forecasting power for GDP growth very similar to FIRM (Tables 2 and 3). For brevity, in the remainder of the paper, we will focus our discussion on firm-level idiosyncratic volatility.[9]

The default premium, DEF, also performs quite well. Its coefficient is positive in six countries and significant or marginally significant in four countries. The other variables, however, have much weaker predictive power. The term premium, TERM, is significant or marginally significant only for Japan and Canada; the stochastically detrended risk-free rate, RREL, is marginally significant only for Japan; aggregate stock market volatility, MV, is significant or marginally significant only for Canada and France; the excess stock market return, ERET, is significant only for Germany and the U.K.; and the consumption-wealth ratio, CAY, and the dividend yield, DP, are always insignificant.

For robustness, we also use log stock market volatility, LMV, log firm-level idiosyncratic volatility, LFIRM, and log industry-level idiosyncratic volatility, LIND, as forecasting variables. Table 4 shows that the results for the log transformations are essentially the same as those for levels. For brevity, in the remainder of the paper, we will focus our discussion on log volatility.

Although it is statistically significant, the explanatory power of LFIRM and DEF is rather moderate in quarterly data; for example, the adjusted R-squared is below 10%. Meese and Rogoff (1983) and Mark (1995), among others, show that the predictive ability of monetary

[9] Davis and Haltiwanger (2001), for example, argue that the firm-level data provide a better measure of the cross-sectional dispersion than the industry-level data. In this paper, we find essentially the same results using both industry- and firm-level idiosyncratic volatilities.

fundamentals increases with forecasting horizons and this interesting pattern is possibly due to a nonlinear forecasting relation (e.g., Kilian and Taylor [2003]). To explore this issue, we repeat the regression analysis using semi-annual data and report the results in Table 5. It is important to note that, unlike Mark (1995), for example, we use *non-overlapping* data since we have many more observations than he did. This difference is important because, as stressed by Kilian (1999), the overlapping data might introduce additional complications that cannot be easily dealt with and thus make the results difficult to interpret.

Consistent with Meese and Rogoff (1983) and Mark (1995), among others, Table 5 shows that the predictive power of LFIRM does increase with forecasting horizons. The difference between quarterly and semi-annual data is quite substantial. In semi-annual data, LFIRM is positive and statistically significant at the 1% level for all countries except Canada, with an average adjusted R-squared of about 15%. These results overwhelmingly reject the notion that foreign exchange rates follow a random walk. Similarly, LMV is also positive and significant for all countries except Canada, although its explanatory power is noticeably weaker than LFIRM. DEF is also significant or marginally significant in most countries. However, again, the other financial variables exhibit negligible predictive abilities, except that TERM is significant for Canada and Japan.

Lastly, we conduct the regression analysis using the non-overlapping annual data and report the results in Table 6. Again, LFIRM is a strong predictor of the change in nominal exchange rates. It is positive and statistically significant in all countries except Canada, with an average adjusted R-squared of about 17%. Meanwhile, DEF remains significant for France, Italy, and the U.K. and LMV is marginally significant for France, Germany, and Italy. Again, we do not observe significant predictive power for the other financial variables except that CAY is marginally significant for Germany and Switzerland.

To summarize, the in-sample regression analysis indicates that industry- and firm-level idiosyncratic volatilities have strong explanatory power for the change in exchange rates, especially over relatively long horizons.

B. Multivariate Regressions

Because the forecasting variables have sizable cross-correlations (Table 1), it is possible that DEF and LMV forecast exchange rates because of their co-movements with LFIRM. Also, the other variables are found to be insignificant, possibly because of an omitted variables problem. To address these issues, we conduct the regression analysis using a financial variable jointly with LFIRM as independent variables. To conserve space, we report only the results for DEF and LMV in Table 7 but briefly summarize the results for the other variables. We find no significant changes for CAY, DP, TERM, RREL, and ERET when they are combined with LFIRM. However, LFIRM and LIND both become insignificant because of the multicollinearity problem. The latter result suggests that LFIRM and LIND contain similar information about future exchange rates, as they also do for GDP growth.

Table 7 shows that LMV loses its predictive power after we control for LFIRM in all cases except the quarterly Canadian rate, for which the effect of LMV is significantly negative.[10] In contrast, LFIRM remains significant or marginally significant in most countries. Therefore, LMV forecasts exchange rates mainly because of its co-movements with LFIRM. It is worth

[10] The Canadian dollar rate is negatively related to past stock market volatility possibly because of its strong negative correlation with U.S. stock market returns. In contrast, the other exchange rates are not correlated with stock market returns.

noting that these patterns are very similar to those obtained from the exercise of forecasting GDP growth (Tables 2 and 3). This casual observation suggests that exchange rate predictability is closely related to economic fundamentals. To conserve space, we do not report the results for LMV for the remainder of the paper because they are similar to those of LFIRM.

However, in Table 7 DEF provides additional information beyond LFIRM for France, Italy and the U.K. In particular, compared with the results in Tables 4 to 6, the improvement is also quite substantial for the U.K. These results indicate that DEF and LFIRM might track different fundamentals in monetary models. Indeed, while LFIRM is a strong predictor of GDP growth, it does not forecast aggregate money. In contrast, while DEF has negligible predictive power for GDP growth, it provides important information about future monetary aggregates in the U.S. and some foreign countries. Of course, DEF forecasts exchange rates possibly because it tracks other economic fundamentals or the time-varying risk premium.

VI. Robustness Checks

In Section V, we show that industry- or firm-level idiosyncratic volatility has significant in-sample explanatory power for the change in U.S. dollar rates against major foreign currencies. This result appears to be consistent with economic theory because idiosyncratic volatility is closely related to fundamentals in U.S. and foreign countries. In this section, we provide further evidence that our results are robust to a number of tests and thus cannot be completely attributed to data mining or spurious regression.

A. Subsamples

To investigate whether the main finding is stable over time, we report in Table 8 the regression results using two subsamples: 1973-85 and 1986-98. To conserve space, we report only the results for log firm-level idiosyncratic volatility, LFIRM, which is the main focus of the paper. The explanatory power of LFIRM is strikingly stable: It remains positive and significant or marginally significant for most countries in both subsamples over various horizons. For example, in semi-annual data, LFIRM is significant in all countries except Canada in the first half of the sample and is significant or marginally significant in five countries in the second half of the sample. Nevertheless, we note that the predictability of the Japanese yen is never significant in the second half of the sample, possibly because of the dramatic developments in Japanese housing and equity markets. Also, as we will show below, Japanese idiosyncratic volatility has a significant effect on its exchange rates.

B. Exchange Rates of OECD Countries in Full Sample

In Table 9 we investigate the explanatory power of DEF and LFIRM for the change in nominal exchange rates of most OECD countries using all available data. In particular, the sample spans the period 1973-1998 for euro area countries and 1973-2003 for the others. We exclude Eastern European countries, including the Czech Republic, Hungary, Poland, and Slovakia. We also exclude emerging markets—Korea, Mexico, and Turkey—because they have maintained fixed exchange rates for an extended period. Lastly, we do not report the results for France, Germany, and Italy, which are the same as those in Tables 4 to 6.

Despite five years of additional data, the results for Canada, Japan, Switzerland, and the U.K. are essentially the same as those reported in Tables 4 to 6. For example, LFIRM is highly significant in semi-annual data for Japan, Switzerland, and the U.K. but not for Canada. Similarly, DEF is highly significant for the U.K. at all horizons.

More importantly, DEF and LFIRM have strong explanatory power for exchange rates of most OECD countries. Of the 19 countries reported in Table 9, DEF is significant for 11 countries and marginally significant for four countries with quarterly data; similarly, LFIRM is significant for 13 countries and marginally significant for one country. Again, their predictive power appears to be complementary: In the multivariate regression, both variables are insignificant in only Australia and Canada. Moreover, the forecasting power is noticeably stronger in semi-annual data than quarterly data. Also, both variables remain significant in annual data for many countries. To summarize, DEF and LFIRM have strong explanatory power for the U.S. dollar rate against currencies of most OECD countries. The expanded international evidence reinforces the suggestion that the predictive results we find are not a mere artifact of data.

C. Out-of-Sample Forecast

In this subsection, we compare the out-of-sample forecast of LFIRM and DEF with the benchmark of a random walk model. Given that many exchange rates exhibit a trend, as documented in Table 1, we allow for a drift in the benchmark model; nevertheless, we find essentially the same results without the drift. The benchmark model and the alternative forecasting model are specified in equations (11) and (12), respectively:

(11) $\Delta S_t = c + \varepsilon_t$

(12) $\Delta S_t = c + b * x_{t-1} + \zeta_t$,

where ΔS_t is the change in nominal foreign exchange rate, x_{t-1} is the forecasting variable(s), c and b are coefficients, and ε_t and ζ_t are forecasting errors. Note that equation (12) is essentially the same as equation (10).

We focus on semi-annual data. To address the small sample problem, we also conduct a bootstrapping analysis similar to Lettau and Ludvigson (2001) and Goyal and Santa-Clara (2003), among many others. In particular, the data-generating process of exchange rates is assumed to be described by equation (11). The forecasting variable(s) follows a VAR process of order one:

(13) $X_t = c + d * X_{t-1} + e * \Delta S_{t-1} + \eta_t$.

In equation (13) we also include the lagged change in nominal exchange rates; however, we find essentially the same results by excluding it. We estimate equations (11) and (13) 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.

Following 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. We use the standard mean-squared-error (MSE) ratio MSE_A / MSE_B, the encompassing (ENC-NEW) test proposed by Clark and McCraken (2001), and the equal forecasting ability (MSE-F) test proposed by McCraken (1999). As shown by Clark and McCracken (2001), the ENC-NEW and MSE-F tests have good size and power properties. For these two tests, the 5% critical values are obtained from the bootstrapping method discussed above.

We report the results for the six G7 countries and Switzerland over the period 1973 to 1998 in Table 10. Consistent with the in-sample regression results, the default premium, DEF, has a smaller MSE than the benchmark model for France, Italy, and the U.K. (panel A). However, the difference is statistically significant only for France and the U.K. in the ENC-NEW test and for France in the MSE-F test. In contrast, we find compelling out-of-sample predictive power using log firm-level idiosyncratic volatility, LFIRM (panel B). It has substantially smaller MSE than the benchmark model for all countries except Canada. More importantly, the difference is statistically significant at the 5% level for all countries except Canada and Japan in the ENC-NEW test and Canada in the MSE-F test. When we include both DEF and LFIRM as forecasting variables (panel C), the results are essentially the same as those reported in panel B except for some improvements in France and the U.K.

To investigate whether the introduction of the euro has had any effect on exchange rate predictability, we repeat the above analysis using the full sample 1973-2003 for Canada, Japan, Switzerland, and the U.K. The results are essentially the same, as shown in Table 11. LFIRM has a smaller MSE than the benchmark model in all countries except Canada. The difference is statistically significant except for Canada in the ENC-NEW test and Canada and the U.K. in the MSE-F test. Again, when we use both DEF and LFIRM as predictors, the predictability of the British pound rate improves noticeably, as shown in Panel C.

To summarize, in sharp contrast with extant evidence, our results indicate that foreign exchange rates are predictable out of sample.

D. Data Mining

It is arguable that our empirical specification is potentially vulnerable to the criticism of data mining. To address this issue, we use the bootstrap procedure proposed by Rapach and Wohar (2006). In particular, we assume that the information set includes a total of 8 forecasting variables: CAY, DP, DEF, TERM, RREL, ERET, LMV, and LFIRM. We exclude LIND because its forecasting power is essentially the same as that of LFIRM; however, including it doesn't change our results in any qualitatively manner. Under the null hypothesis, we assume that exchange rates follow a random walk, as in equation (11). We assume that each of the forecasting variables follows the process in equation (13). We estimate these processes using the actual data and then simulate the processes using the estimated parameters and errors. To conserve the cross-sectional dependence, in simulation, we draw the error terms of all variables from the same period. For each set of simulated data, we calculate t-statistics, for example, for each of 8 variables and save the maximal t-statistic. We repeat the analysis 10,000 times and use the 10,000 maximal t-statistics as a proxy for the empirical t-distribution, in which we explicitly control for data mining. Similarly, we obtain the empirical distributions for the ENC-NEW test and MSE-F test statistics.

Table 12 reports the bootstrapping critical values for semi-annual data over the period 1973 to 1998. Tables 5 and 12 indicate that LFIRM remains significant at least at the 5% level for France, Germany, Italy, Japan, Switzerland, and U.K., even after we explicitly take into account data mining. Similarly, Tables 10 and 12 show that the out-of-sample forecasting power of LFIRM remains significant at the 5% level for France, Germany, Switzerland and Italy, and at the 10% level for U.K. To summarize, our main results are robust to the consideration of data mining.

E. Country-Specific Idiosyncratic Volatility

We include both the U.S. and foreign country's firm-level idiosyncratic volatilities as independent variables and report the OLS regression results in Table 13.[11] The results are consistent with those obtained using U.S. idiosyncratic volatility, which is now denoted by LFIRM_US. For example, idiosyncratic volatility in foreign countries, LFIRM_L, has a negative coefficient in the forecasting regression for most exchange rates, indicating that a high level of foreign idiosyncratic volatility is usually associated with a future appreciation of its own currency.[12] The relation is particularly strong for Germany, of which idiosyncratic volatility is marginally significant in quarterly data and significant in semi-annual and annual data. Compared with the results reported in Tables 4 to 6, the improvements associated with German idiosyncratic volatility are quite substantial, especially over relatively long horizons. For example, with annual data, the adjusted R-squared is 40% in Table 12, compared with 32% in Table 6. We find a similar result for Japan in annual data. In particular, Japanese idiosyncratic volatility is negative and highly significant, with an adjusted R-squared of 26%, compared with only 8% in Table 6. Moreover, the French idiosyncratic volatility is also negative and marginally significant in semi-annual data.

To summarize, we find similar results using country-specific idiosyncratic volatility, indicating that our results cannot be mainly attributed to data mining or spurious regression.

---

[11] See Appendix B for details about the construction of idiosyncratic volatility in these counties.
[12] It should be noted that exchange rates are denoted as prices of The U.S. dollar in foreign currencies.

F. Discussion

We find that a relatively high level of U.S. idiosyncratic volatility is usually associated with an appreciation of the U.S. dollar. This result implies that, as indicated by equation (10), U.S. idiosyncratic volatility should have a more negative effect on fundamentals in foreign countries than in the U.S. Indeed, we find that the absolute effect of firm-level idiosyncratic volatility for Germany and Japan is almost twice as high as that for U.S. (Table 3), although the difference is not statistically significant. The effect of idiosyncratic volatility for the other countries, however, is quite similar to that for U.S. One possible explanation for the latter result is that the Bundesbank exerts great influence on the monetary policy in many European countries, including France, Italy, and U.K. (e.g., Clarida, Gali, and Gertler [1998]). Therefore, it should not be too surprising that the exchange rates in these countries move closely with each other, as shown in Table 1. Overall, these results suggest that monetary fundamentals might go in the right direction in explaining exchange rate predictability but might not be the only explanation. For example, we might have omitted some important fundamentals, which are significantly influenced by idiosyncratic volatility. Also, idiosyncratic volatility forecasts exchange rates possibly because of a time-varying risk premium.

VII. Conclusion

In this paper, we show that U.S. idiosyncratic volatility forecasts exchange rates of the U.S. dollar against major foreign currencies. These results appear to be quite robust to using (1) different sample periods, (2) most OECD countries' currencies, (3) out-of-sample tests, (4) a bootstrap procedure to explicitly account for data mining, and (5) country-specific idiosyncratic volatility. Our empirical analysis suggests that, in sharp contrast with most existing empirical results, foreign exchange rates don't follow a random walk.

We also document a strong link between exchange rate predictability and economic fundamentals. Early authors, e.g., Lilien (1982), Loungani, Rush, and Tave (1990), CLMX, and Comin and Philippon (2005), find that idiosyncratic volatility has a significant effect on real economic activity. In this paper, we show that, among all the financial variables, only U.S. idiosyncratic volatility forecasts GDP growth in both U.S. and foreign countries. This result is potentially consistent with monetary models, in which the nominal exchange rate is determined by the expected discounted value of future fundamentals. However, it might also reflect a time-varying risk premium. A further investigation of these issues is crucial for understanding the dynamics of foreign exchange rates, and we leave it for future research.

References

Almeida, A., C. Goodhart, and R. Payne, 1998, The Effects of Macroeconomic News on High Frequency Exchange Rate Behavior, Journal of Financial and Quantitative Analysis, 33, 383-408.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega, 2003, Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange, American Economic Review, 93, 38-62.

Andersen, T., T. Bollerslev, F. Diebold and C. Vega, 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. and L. Giorgianni, 2001, Long-Horizon Exchange Rate Predictability? Review of Economics and Statistics, 83, 81-91.

Bernanke, B., and A. Blinder, 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 Jacob A. Frenkel and Harry G. Johnson, eds., The Economics of Exchange Rates: Selected Studies. Reading, MA: Addison-Wesley, 75-96.

Boudoukh, J., M. Richardson, and R. Whitelaw, 2005, The Information in Long-Maturity Forward Rates: Implications for Exchange Rates and the Forward Premium Anomaly, Unpublished Working Paper, NYU.

Campbell, J., M. Lettau, B. Malkiel, and Y. Xu, 2001, Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk, Journal of Finance, 56, 1-43.

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

Clark, T., and M. McCracken, 2001, Tests of Equal Forecast Accuracy and Encompassing for Nested Models, Journal of Econometrics, 105, 85-110.

Clarida, R., and M. Taylor, 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.

Clarida, R., Gali, J., Gertler, M., 1998, Monetary policy rules in practice: some international evidence, European Economic Review, 42, 1033-1067.

Comin, D., and T. Philippon, 2005, The Rise in Firm-Level Volatility: Causes and Consequences, NBER Macroeconomics Annual, 20, edited by M. Gertler and K. Rogoff.

Davis, S., and J. Haltiwanger, 2001, Sectoral Job Creation and Destruction Responses to Oil Price Changes, Journal of Monetary Economics, 48, 465-512.

Dornbusch, R., 1976, Expectations and Exchange Rate Dynamics, Journal of Political Economy, 84, 1161-1176.

Engel, C. and J. Hamilton, 1990, Long Swings in the Dollar: Are They in the Data and Do Markets Know It? American Economic Review, 80, 689-713.

Engel, C. and K. West, 2004, Exchange Rates and Fundamentals, forthcoming, Journal of Political Economy.

Evans, M. and R. Lyons, 2005a, Meese-Rogoff Redux: Micro-Based Exchange Rate Forecasting, forthcoming, American Economic Review Papers and & Proceedings.

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

Fama, E., and K. French, 1989, Business Conditions and Expected Returns on Stocks and Bonds, Journal of Financial Economics, 25, 23-49.

Fama, E., and K. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, Journal of Financial Economics, 33, 3-56.

Faust, J., J. Rogers, and J. Wright, 2003, Exchange Rate Forecasting: The Errors We've Really Made, Journal of International Economics, 60, 35-59.

Ferson, W., S Sarkissian, and T. Simin, 2003, Spurious Regressions in Financial Economics?, Journal of Finance, 58, 1393-1414.

French, K., R. Stambaugh, and W. Schwert, 1987, Expected Stock Returns and Volatility, Journal of Financial Economics, 19, 3-29.

Frenkel, J., 1976, A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence, Scandinavian Journal of Economics, 78, 200-224.

Ghysels, E., P. Santa-Clara, and R. Valkanov, 2005, There is a Risk-Return Tradeoff After All, forthcoming, Journal of Financial Economics.

Goodhart, C., S. Hall, S., Henry, and B. Pesaran 1993, News Effects in a High-Frequency Model of the Sterling-Dollar Exchange Rate, 8, Journal of Applied Econometrics, 1-13.

Goyal, A. and P. Santa-Clara, 2003, Idiosyncratic Risk Matters! Journal of Finance, 58, 975-1007.

Guo, H. and R. Whitelaw, 2005, Uncovering the Risk-Return Relation in the Stock Market, forthcoming, Journal of Finance.

Hong, Y., and T. Lee, 2003, Inference on Predictability of Foreign Exchange Rates via Generalized Spectrum and Nonlinear Time Series Models, Review of Economics and Statistics, 85, 1048-1062.

Kaminsky, G., 1993, Is There a Peso Problem? Evidence from the Dollar/Pound Exchange Rate, 1976-1987, American Economic Review, 83, 450-472.

Kilian, L., 1999, Exchange Rates and Monetary Fundamentals: What Do we Learn from Long-Horizon Regressions? Journal of Applied Econometrics, 14, 491-510.

Kilian, L. and M. Taylor, 2003, Why Is It so Difficult to Beat the Random Walk Forecast of Exchange Rates? Journal of International Economics, 60, 85-107.

Lettau, M., and S. Ludvigson, 2001, Consumption, Aggregate, Wealth and Expected Stock Returns, Journal of Finance, 56, 815-49.

Lettau, M., and S. Ludvigson, 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., M. Rush, and W. Tave, 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. and K. Rogoff, 1983, Empirical Exchange Rate Models of the 1970's: Do They Fit Out of Sample? Journal of International Economics, 14, 3-24.

Meese, R., 1990, Currency Fluctuations in the Post-Bretton Woods Era, Journal of Economic Perspective, 117-134.

Merton, R., 1980, On Estimating the Expected Return on the Market: An Exploratory Investigation, Journal of Financial Economics, 8, 323-61.

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.

Obstfeld, M. and K. Rogoff, 1996, Foundations of International Economics, MIT Press, Cambridge, MA.

Rapach, D., and M. Wohar, 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., and M. Watson, 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.

Appendix A. Derivation of Equations (5) and (6)

We can rewrite $(1-b)\sum_{i=0}^{\infty} b^i E_t(f_{t+i})$ as

(A1) $F_t = (1-b)\sum_{i=0}^{\infty} b^i E_t(f_{t+i}) = (1-b)E_t(f_t + bf_{t+1} + b^2 f_{t+2} + b^3 f_{t+3} + ... + b^i f_{t+i} + ...)$.

Substituting equation (2) into equation (A1), we obtain

(A2)
$$\begin{aligned} &F_t = (1-b) f_t + \\ &b(1-b)E_t(f_t + b^1 f_{t+1} + b^2 f_{t+2} + b^3 f_{t+3} + ... + b^i f_{t+i} + ...) \\ &+b\gamma(1-b)E_t(x_t + bx_{t+1} + b^2 x_{t+2} + b^3 x_{t+3} + ... + b^i x_{t+i} + ...) \\ &= (1-b) f_t + bF_t + b\gamma(1-b)E_t(x_t + bx_{t+1} + b^2 x_{t+2} + b^3 x_{t+3} + ... + b^i x_{t+i} + ...) \end{aligned} .$$

Note that we use the relation $E_t(\varepsilon_{t+i}) = 0, \quad i = 1,2,3...\infty$ in the derivation of equation (A2).

Denote

(A3) $X_t = E_t(x_t + bx_{t+1} + b^2 x_{t+2} + b^3 x_{t+3} + ... + b^i x_{t+i} + ...)$.

Substituting equation (4) into equation (A3), we obtain

(A4) $X_t = x_t + b\beta E_t(x_t + bx_{t+1} + b^2 x_{t+2} + b^3 x_{t+3} + ... + b^i x_{t+i} + ...) = x_t + b\beta X_t$.

We use the relation $E_t(\eta_{t+i}) = 0, \quad i = 1,2,3...\infty$ in the derivation of equation (A4). We can rewrite equation (A4) as

(A5) $X_t = \dfrac{1}{1-b\beta} x_t$.

Substituting equation (A5) into equation (A2), we obtain

(A6) $F_t = (1-b)\sum_{i=0}^{\infty} b^i E_t(f_{t+i}) = f_t + \dfrac{b\gamma}{1-b\beta} x_t$.

Similarly, we can show

(A7) $F_t^* = (1-b)\sum_{i=0}^{\infty} b^i E_t(f_{t+i}^*) = f_t^* + \dfrac{b\gamma^*}{1-b\beta} x_t$.

Appendix B. Construction of Average Firm-Level Idiosyncratic Volatility

We obtain daily value-weighted stock market return and daily individual stock return data from the CRSP database for U.S. over the period July 1962 to December 2003. We obtain the same variables denominated in local currencies from Datastream over the period January 1965 to December 2003 for the U.K. and over the period January 1973 to December 2003 for Canada, France, Germany, Italy, and Japan. As in CLMX, we assume that the daily risk-free rate is the rate which, over the number of calendar days, compounds to the monthly T-bill rate. The monthly T-bill rate is obtained from IFS for all countries.

We follow CLMX and Goyal and Santa-Clara (2003), among others, in the construction of average firm-level idiosyncratic volatility. We define quarterly value-weighted idiosyncratic volatility as

$$\text{(B1)} \qquad VWIV_t = \sum_{i=1}^{N_t} \omega_{it}\Big[\sum_{d=1}^{D_{it}} \eta_{id}^2 + 2\sum_{d=2}^{D_{it}} \eta_{id}\eta_{id-1}\Big] \quad and \quad \omega_{it} = \frac{v_{it-1}}{\sum_{j=1}^{N_t} v_{jt-1}}$$

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. As in CLMX and Goyal and Santa-Clara (2003), we use the CAPM to control for systematic risk in this paper. The idiosyncratic shock η_{id} is thus 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 the excess stock market return, e_{md}[B1]:

[B1] We do not use the more elaborate Fama and French (1993) three-factor model because the daily factor data are directly available only for U.S. Moreover, there is an on-going debate whether the additional risk factors reflect systematic risk or data mining. Nevertheless, the additional factors are unlikely to affect our results in any qualitative manner because we find essentially the same results for U.S. by controlling for systematic risk using

(B2) $er_{id} = \alpha + \beta \cdot e_{md} + \eta_{id}$.

Given that factor loadings β may change over time, we estimate equation (B2) using a rolling sample. For example, the idiosyncratic shock at time d is equal to $er_{id} - \hat{\alpha} - \hat{\beta} \cdot f_d$, where we obtain the coefficient estimates $\hat{\alpha}$ and $\hat{\beta}$ using the daily data from d-130 to d-1. We require a minimum of 45 daily observations in order to obtain less-noisy parameter estimates. As in Goyal and Santa-Clara (2003), we exclude stocks that have less than 8 return observations in a quarter and drop the term $2\sum_{d=2}^{D_{it}} r_{id} r_{id-1}$ from equation (B1) if $\sum_{d=1}^{D_{it}} r_{id}^2 + 2\sum_{d=2}^{D_{it}} r_{id} r_{id-1}$ is less than zero. We also drop stocks for which the market capitalization data at the end of previous quarter are missing.

We impose some additional filters for the Datastream data for potential errors. (1) The return index (Datastream variable RI) is rounded off by Datastream to the nearest tenth and this rounding introduces substantial errors in returns of low RI stocks. Therefore, if the return index of a stock is below 3 in a day, we set the corresponding return to a missing value for that day.[B2] (2) If the return on a stock is greater than 300% in a day, we set that return to a missing value. (3) If the absolute value of changes in capitalization is more than 50% in one day, the return for this stock is set to a missing value on that day. (4) If the price of a stock falls by more than 90% in a day and it has increased by more than 200% within the previous 20 days—approximately a trading month, we set the returns between the two dates to missing values. (5) If the price of a stock increases by more than 100% in a day and has decreased by more than 200% within the previous 20 days, we set the returns between the two dates to missing values.

---

daily Fama and French three factors obtained from Professor Kenneth French at Dartmouth College. To converse space, these results are not reported here but available upon request.

[B2] The beginning value of RI for all stocks in Datastream is set to 100. RI of 3 indicates that the firm has lost 97% of its value over its life.

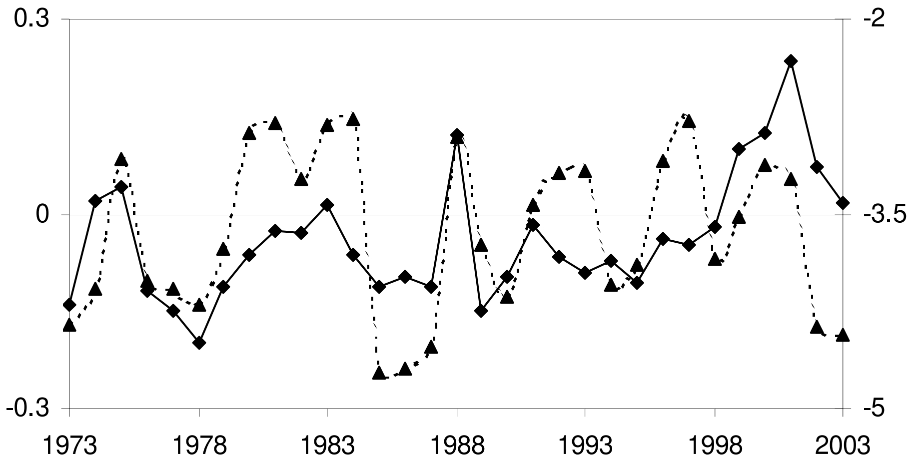

Figure 1 Log Average Firm-Level Idiosyncratic Volatility (Solid Line, Right Scale) vs. Changes in Deutsche Mark Rate (1973-98) and euro Rate (1999-2003) One-Year Forward

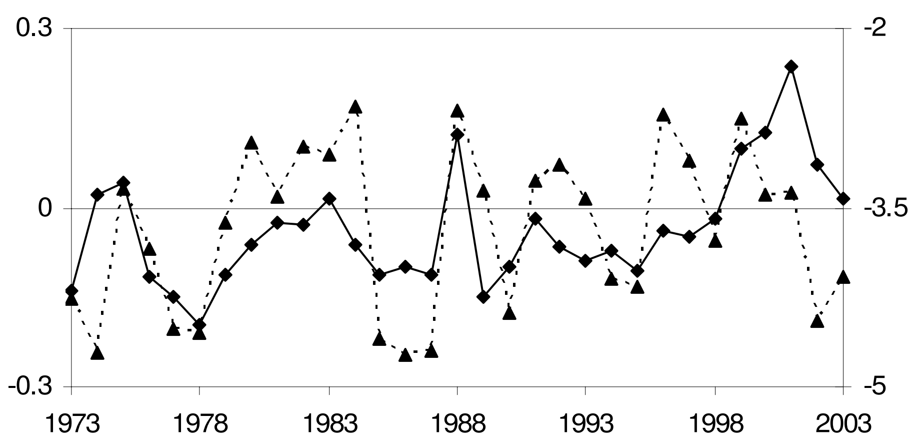

Figure 2 Log Average Firm-Level Idiosyncratic Volatility (Solid Line, Right Scale) vs. Changes in Swiss Franc Rate One-Year Forward

Table 1 Summary Statistics

Panel A Changes in Nominal Exchange Rates

	Canada	France	Germany	Italy	Japan	Switzerland	U.K.
			Univariate Statistics				
Mean	0.004	0.001	-0.006	0.010	-0.009	-0.010	0.003
Standard Deviation	0.021	0.060	0.064	0.057	0.063	0.071	0.054
Auto-Correlation	0.040	0.165	0.096	0.171	0.135	0.060	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		
Switzerland	0.04	0.85	0.89	0.67	0.64	1.00	
U.K.	0.13	0.68	0.66	0.66	0.49	0.62	1.00

Panel B Forecasting Variables

	CAY	DP	DEF	TERM	RREL	MV	FIRM	IND	ERET
				Univariate Statistics					
Auto-Correlation	0.84	0.97	0.90	0.78	0.72	0.52	0.83	0.83	0.04
				Cross-Correlation					
CAY	1.00								
DP	0.32	1.00							
DEF	0.05	0.57	1.00						
TERM	0.32	-0.02	0.26	1.00					
RREL	-0.05	0.08	-0.34	-0.62	1.00				
MV	-0.15	-0.20	0.17	-0.06	-0.12	1.00			
FIRM	-0.34	-0.41	0.11	-0.09	-0.09	0.76	1.00		
IND	-0.33	-0.39	0.06	-0.13	-0.04	0.70	0.92	1.00	
ERET	-0.05	-0.07	0.13	0.15	-0.26	-0.38	-0.18	-0.21	1.00

Notes: The table reports summary statistics for quarterly changes in nominal exchange rates (panel A) and U.S. financial variables (panel B) over the sample period 1973:Q1 to 1998:Q4. CAY is the consumption-wealth ratio; DP is the dividend yield on the S&P 500 index; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills; MV is realized stock market volatility; FIRM is average firm-level idiosyncratic stock volatility; IND is average industry-level idiosyncratic stock volatility; and ERET is the excess stock market return.

Table 2 Forecasting Growth Rate of U.S. GDP: 1963:Q1 to 2003:Q4

	X(-1)	t-value	DGDP(-1)	t-value	ARSQ
			Panel A Quarterly Data		
DEF	-0.002	-1.087	0.244***	2.939	0.072
TERM	0.001**	2.011	0.260***	3.091	0.092
DP	-0.001	-1.142	0.257***	3.252	0.073
RREL	0.000	-0.545	0.290***	3.337	0.066
CAY	-0.012	-0.299	0.270***	3.345	0.063
ERET	0.019**	2.593	0.267***	3.264	0.101
MV	-0.421***	-3.552	0.227***	2.788	0.115
FIRM	-0.111**	-2.295	0.237***	2.896	0.097
IND	-0.389***	-2.778	0.235***	2.903	0.097
LMV	-0.003***	-3.569	0.191**	2.284	0.129
LFIRM	-0.004***	-3.318	0.209**	2.526	0.122
LIND	-0.003***	-3.367	0.191**	2.300	0.124
			Panel B Semi-Annual Data		
DEF	0.001	0.188	0.402***	3.861	0.132
TERM	0.003**	3.143	0.384***	3.976	0.223
DP	-0.100	-0.860	0.376***	3.622	0.139
RREL	-0.004**	-2.489	0.532***	5.602	0.219
CAY	0.001	0.012	0.392***	3.621	0.131
ERET	0.057***	3.889	0.402***	4.365	0.252
MV	-0.528**	-2.433	0.343***	3.212	0.167
FIRM	-0.174***	-3.108	0.351***	3.310	0.167
IND	-0.599***	-3.542	0.351***	3.267	0.168
LMV	-0.004***	-2.715	0.312***	2.884	0.176
LFIRM	-0.007***	-2.813	0.315***	2.902	0.184
LIND	-0.004	-2.445	0.322***	2.925	0.168
			Panel C Annual Data		
DEF	0.000	0.022	0.220	1.452	-0.004
TERM	0.005**	2.465	0.205	1.365	0.124
DP	-0.001	-0.358	0.207	1.306	0.000
RREL	-0.005	-1.412	0.307**	2.565	0.070
CAY	0.180	0.758	0.247	1.453	0.009
ERET	0.096*	1.948	0.310**	2.219	0.112
MV	-0.474	-0.907	0.184	1.104	0.011
FIRM	-0.356***	-2.808	0.152	0.928	0.064
IND	-1.315***	-3.809	0.158	0.994	0.066
LMV	-0.006	-1.475	0.113	0.656	0.048
LFIRM	-0.015**	-2.440	0.091	0.533	0.101
LIND	-0.010***	-2.349	0.105	0.653	0.083

Notes: This table reports the OLS estimation results of regressing the growth rate of U.S. GDP on its one-period lag and various lagged U.S. financial variables. The column under "X(-1)" is the point estimate of the coefficient for the financial variable listed in the first column and the column under "DGDP(-1)" is the point estimate of the coefficient for the lagged dependent variable. We report the White-corrected standard t-statistic under the columns "t-value" and the adjusted R-squared under the column "ARSQ". ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. CAY is the consumption-wealth ratio; DP is the dividend yield on the S&P 500 index; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills; MV is realized stock market volatility; FIRM is average firm-level idiosyncratic stock volatility; IND is average industry-level idiosyncratic stock volatility; ERET is the excess stock market return; LMV is log realized stock market volatility; LFIRM is log average firm-level idiosyncratic stock volatility; and LIND is log average industry-level idiosyncratic stock volatility. Panel A uses quarterly data; panel B uses non-overlapping semi-annual data; and panel C uses non-overlapping annual data.

Table 3 Forecasting Quarterly Growth Rate of GDP in G7 Countries: 1963:Q1 to 1999:Q4

	X(-1)	t-value	DGDP(-1)	t-value	ARSQ
			TERM		
Canada	0.000	0.671	0.340***	3.920	0.103
France	0.000	0.539	0.311***	3.729	0.083
Germany	0.000	-0.242	-0.189	-1.578	0.022
Italy	-0.001	-0.943	0.367***	3.587	0.140
Japan	-0.001	-1.305	0.321***	3.603	0.112
U.K.	0.002**	2.172	-0.030	-0.298	0.022
U.S.	0.001**	1.990	0.274***	3.109	0.101
			ERET		
Canada	0.011	1.214	0.335***	3.946	0.110
France	0.010	1.134	0.338***	4.037	0.097
Germany	0.008	0.593	-0.181	-1.458	0.025
Italy	0.015	1.423	0.399***	3.741	0.148
Japan	0.011	0.909	0.349***	3.824	0.109
U.K.	0.016	1.347	0.009	0.081	0.003
U.S.	0.019**	2.213	0.290***	3.389	0.101
			LMV		
Canada	-0.002	-1.515	0.317***	3.701	0.123
France	-0.001	-0.860	0.303***	3.632	0.088
Germany	-0.003**	-2.370	-0.234***	-2.051	0.056
Italy	-0.003	-1.560	0.367***	3.483	0.172
Japan	-0.003**	-2.044	0.276***	3.001	0.116
U.K.	-0.003**	-2.542	-0.038	-0.340	0.032
U.S.	-0.003***	-2.656	0.221***	2.529	0.119
			LFIRM		
Canada	-0.003	-1.615	0.308***	3.486	0.123
France	-0.004*	-1.915	0.257***	2.902	0.116
Germany	-0.009***	-4.274	-0.266**	-2.309	0.104
Italy	-0.005**	-2.335	0.347***	3.360	0.173
Japan	-0.009***	-3.240	0.218**	2.457	0.160
U.K.	-0.004**	-2.036	-0.033	-0.288	0.013
U.S.	-0.005**	-2.331	0.230**	2.578	0.113
			LIND		
Canada	-0.003*	-1.780	0.304***	3.506	0.128
France	-0.002*	-1.710	0.271***	3.091	0.101
Germany	-0.008***	-4.801	-0.273**	-2.442	0.120
Italy	-0.004***	-2.909	0.355***	3.480	0.170
Japan	-0.005**	-2.623	0.261***	2.894	0.126
U.K.	-0.005***	-2.656	-0.048	-0.433	0.036
U.S.	-0.004**	-2.264	0.211**	2.357	0.118

Notes: This table reports the OLS estimation results of regressing the quarterly GDP growth rate of GDP in G7 countries using its one-period lag and various U.S. financial variables. See notes of Table 2 for more details.

Table 4 Forecasting Quarterly Changes in Exchange Rates: 1973 to 1998

Country	CAY	t-value	ARSQ	DP	t-value	ARSQ	DEF	t-value	ARSQ
Canada	-0.033	-0.204	-0.009	0.000	-0.102	-0.010	-0.003	-0.721	-0.004
France	-0.309	-0.501	-0.006	0.006	1.245	0.003	0.030**	2.362	0.049
Germany	0.204	0.302	-0.008	0.002	0.475	-0.008	0.022*	1.828	0.018
Italy	-0.457	-1.027	-0.001	0.007	1.561	0.007	0.027**	2.240	0.040
Japan	-0.106	-0.197	-0.009	0.000	0.035	-0.010	0.000	0.006	-0.010
Switzerland	0.282	0.456	-0.008	0.001	0.086	-0.010	0.021	1.607	0.011
U.K.	-0.366	-0.890	-0.003	0.004	1.059	-0.002	0.033***	3.613	0.078

	TERM	t-value	ARSQ	RREL	t-value	ARSQ	ERET	t-value	ARSQ
Canada	0.002*	1.773	0.015	-0.786	-1.503	0.006	0.035	1.377	0.010
France	-0.002	-0.492	-0.007	0.020	0.009	-0.010	0.070	1.158	0.000
Germany	-0.002	-0.393	-0.008	-0.191	-0.093	-0.010	0.140**	2.216	0.026
Italy	0.001	0.182	-0.009	0.146	0.086	-0.010	0.058	1.222	-0.002
Japan	-0.010**	-2.147	0.046	3.329*	1.922	0.024	0.049	0.786	-0.005
Switzerland	-0.001	-0.241	-0.009	-1.190	-0.570	-0.006	0.128	1.637	0.014
U.K.	0.001	0.298	-0.009	-0.671	-0.366	-0.008	0.121**	2.516	0.027

	MV	t-value	ARSQ	FIRM	t-value	ARSQ	IND	t-value	ARSQ
Canada	-1.351**	-2.559	0.054	-0.507	-1.446	0.018	-0.247	-0.131	-0.010
France	2.249*	1.834	0.012	1.912***	2.697	0.039	10.438**	2.444	0.052
Germany	1.819	1.448	0.003	2.039***	2.756	0.040	9.061**	2.171	0.032
Italy	1.551	1.618	0.002	1.228**	2.173	0.012	7.174*	1.951	0.022
Japan	0.171	0.098	-0.010	0.594	0.624	-0.006	3.908	0.740	-0.002
Switzerland	2.099	1.266	0.004	1.987**	2.220	0.028	7.941	1.561	0.016
U.K.	1.095	1.101	-0.003	1.431*	1.963	0.024	6.519*	1.675	0.020

	LMV	t-value	ARSQ	LFIRM	t-value	ARSQ	LIND	t-value	ARSQ
Canada	-0.007**	-2.041	0.034	-0.009	-1.280	0.008	0.001	0.111	-0.010
France	0.021**	2.467	0.041	0.048***	3.040	0.051	0.038***	2.916	0.076
Germany	0.017*	1.955	0.023	0.053***	3.140	0.056	0.035***	2.683	0.055
Italy	0.014*	1.888	0.016	0.031**	2.422	0.019	0.027**	2.399	0.037
Japan	0.009	0.804	-0.002	0.022	1.046	0.001	0.017	1.133	0.007
Switzerland	0.018*	1.676	0.018	0.052**	2.507	0.041	0.031*	1.966	0.030
U.K.	0.011	1.639	0.009	0.038**	2.411	0.036	0.024*	1.973	0.032

Notes: The table reports the OLS estimation results of regressing quarterly changes in nominal exchange rates using various U.S. financial variables over the period 1973:Q1 to 1998:Q4, with a total of 104 observations. The White-corrected standard error is used to calculate the t-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. CAY is the consumption-wealth ratio; DP is the dividend yield on the S&P 500 index; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills; RREL is the stochastically detrended risk-free rate; ERET is the excess stock market return; MV is realized stock market volatility; FIRM is average firm-level idiosyncratic volatility; IND is average industry-level idiosyncratic volatility; LMV is log realized stock market volatility; LFIRM is log average firm-level idiosyncratic stock volatility; and LIND is log average industry-level idiosyncratic stock volatility.

Table 5 Forecasting Semi-Annual Changes in Exchange Rates: 1973 to 1998

Country	CAY	t-value	ARSQ	DP	t-value	ARSQ	DEF	t-value	ARSQ
Canada	0.046	0.161	-0.020	-0.001	-0.127	-0.020	-0.006	-0.559	-0.010
France	-0.271	-0.173	-0.019	0.014	1.288	0.005	0.069***	2.815	0.098
Germany	0.831	0.512	-0.010	0.009	0.900	-0.009	0.050**	2.102	0.039
Italy	-0.524	-0.526	-0.015	0.015	1.621	0.011	0.059**	2.671	0.080
Japan	0.551	0.446	-0.016	0.001	0.103	-0.020	0.001	0.028	-0.020
Switzerland	1.220	0.851	0.000	0.006	0.553	-0.016	0.046*	1.741	0.028
U.K.	-0.404	-0.375	-0.017	0.013	1.573	0.007	0.058***	3.151	0.083
	TERM	t-value	ARSQ	RREL	t-value	ARSQ	ERET	t-value	ARSQ
Canada	0.005**	2.030	0.037	-1.640	-1.479	0.010	0.106*	1.708	0.046
France	-0.003	-0.274	-0.018	-1.297	-0.273	-0.018	-0.016	-0.081	-0.020
Germany	-0.003	-0.305	-0.018	-1.279	-0.296	-0.018	-0.016	-0.080	-0.020
Italy	0.002	0.196	-0.019	-0.649	-0.164	-0.019	-0.055	-0.353	-0.018
Japan	-0.017**	-2.078	0.048	6.219	1.511	0.023	-0.180	-1.178	-0.001
Switzerland	0.002	0.218	-0.019	-2.679	-0.665	-0.013	-0.032	-0.142	-0.019
U.K.	-0.002	-0.195	-0.019	-0.205	-0.056	-0.020	-0.534	0.595	-0.017
	MV	t-value	ARSQ	FIRM	t-value	ARSQ	IND	t-value	ARSQ
Canada	-2.103**	-2.109	0.071	-0.867	-1.178	0.023	0.412	0.086	-0.020
France	6.405***	2.738	0.063	5.492***	3.365	0.152	29.402***	3.449	0.182
Germany	7.146***	3.825	0.080	6.063***	4.045	0.181	27.777***	3.106	0.153
Italy	5.223***	3.069	0.043	4.378***	3.770	0.105	24.422***	3.389	0.139
Japan	5.709***	2.823	0.046	3.888***	3.085	0.066	19.784**	2.619	0.071
Switzerland	7.680***	4.274	0.090	6.074***	4.190	0.172	27.307**	2.544	0.140
U.K.	4.175***	3.113	0.024	4.081***	3.356	0.097	18.712***	3.125	0.081
	LMV	t-value	ARSQ	LFIRM	t-value	ARSQ	LIND	t-value	ARSQ
Canada	-0.012	-1.619	0.042	-0.016	-0.893	0.004	0.004	0.296	-0.017
France	0.052**	2.620	0.101	0.141***	3.568	0.173	0.103***	3.573	0.212
Germany	0.054***	2.887	0.107	0.158***	4.285	0.212	0.103***	3.525	0.203
Italy	0.040**	2.592	0.062	0.108***	3.631	0.110	0.087***	3.644	0.167
Japan	0.043**	2.365	0.066	0.102***	3.234	0.081	0.068**	2.436	0.081
Switzerland	0.053***	2.720	0.095	0.155***	3.977	0.195	0.095***	2.852	0.162
U.K.	0.031**	2.324	0.034	0.104***	3.546	0.111	0.065***	2.835	0.096

Notes: The table reports the OLS estimation results of regressing non-overlapping semi-annual changes in nominal exchange rates using U.S. financial variables over the period 1973 to 1998, with a total of 52 observations. See notes of Table 4 for details.

Table 6 Forecasting Annual Changes in Exchange Rates: 1973 to 1998

Country	CAY	t-value	ARSQ	DP	t-value	ARSQ	DEF	t-value	ARSQ
Canada	0.098	0.197	-0.041	-0.001	-0.096	-0.041	-0.015	-1.186	-0.013
France	0.180	0.111	-0.041	0.025	1.177	0.005	0.114***	3.222	0.166
Germany	2.422*	1.718	0.010	0.016	0.732	-0.023	0.062	1.649	0.019
Italy	-1.470	-1.137	-0.023	0.024	1.315	0.000	0.094**	2.699	0.093
Japan	0.587	0.390	-0.039	0.002	0.075	-0.041	-0.008	-0.191	-0.041
Switzerland	3.431*	2.050	0.044	0.012	0.573	-0.032	0.062	1.658	0.008
U.K.	0.011	0.008	-0.042	0.023	1.203	-0.004	0.106***	3.568	0.126

	TERM	t-value	ARSQ	RREL	t-value	ARSQ	ERET	t-value	ARSQ
Canada	0.006	1.351	0.005	-1.655	-0.857	-0.025	0.182	1.666	0.073
France	-0.011	-0.578	-0.024	-5.132	-0.585	-0.023	0.163	0.449	-0.031
Germany	-0.013	-0.820	-0.016	-4.066	-0.558	-0.030	-0.004	-0.012	-0.042
Italy	-0.004	-0.197	-0.040	-3.010	-0.388	-0.035	0.129	0.396	-0.035
Japan	-0.021	-1.477	0.029	10.588	1.348	0.037	-0.388*	-1.714	0.020
Switzerland	0.000	-0.030	-0.042	-5.295	-0.809	-0.025	-0.055	-0.130	-0.041
U.K.	0.002	0.123	-0.041	-3.148	-0.443	-0.035	0.355	1.506	0.008

	MV	t-value	ARSQ	FIRM	t-value	ARSQ	IND	t-value	ARSQ
Canada	-2.939**	-2.223	0.116	-1.673*	-1.736	0.083	-5.018	-0.773	-0.005
France	6.124**	2.496	0.041	6.311***	3.176	0.173	44.638***	4.386	0.315
Germany	7.310***	2.945	0.076	7.370***	3.723	0.249	43.229***	4.146	0.290
Italy	4.317*	1.835	-0.002	4.442**	2.463	0.061	31.481***	2.947	0.129
Japan	4.323	1.701	-0.001	4.212*	1.988	0.052	23.476**	2.268	0.055
Switzerland	7.190**	2.464	0.052	7.389***	3.730	0.200	44.023**	4.763	0.243
U.K.	3.727	1.340	-0.013	4.095*	1.764	0.043	25.656*	2.048	0.068

	LMV	t-value	ARSQ	LFIRM	t-value	ARSQ	LIND	t-value	ARSQ
Canada	-0.017	-1.485	0.056	-0.036	-1.246	0.039	-0.007	-0.335	-0.035
France	0.049*	2.007	0.058	0.189***	3.859	0.231	0.164***	4.710	0.361
Germany	0.051*	2.039	0.067	0.218***	4.906	0.319	0.161***	4.678	0.343
Italy	0.039*	1.747	0.020	0.134***	3.026	0.091	0.120***	3.329	0.166
Japan	0.036	1.622	0.013	0.129**	2.288	0.084	0.082*	1.764	0.058
Switzerland	0.043	1.429	0.023	0.215***	3.784	0.249	0.152***	3.715	0.244
U.K.	0.033	1.558	0.000	0.126**	2.268	0.072	0.086*	1.788	0.062

Notes: The table reports the OLS estimation results of regressing non-overlapping annual changes in nominal exchange rates using financial variables over the period 1973 to 1998, with a total of 26 observations. See notes of Table 4 for details.

Table 7 Multivariate Regressions: 1973 to 1998

Country	DEF	t-value	LFIRM	t-value	ARSQ	LMV	t-value	LFIRM	t-value	ARSQ
Panel A. Quarterly Data										
Canada	-0.002	-0.409	-0.008	-1.107	0.001	-0.013**	-2.571	0.014*	1.694	0.056
France	0.024*	1.893	0.039**	2.566	0.077	0.010	0.933	0.034*	1.867	0.047
Germany	0.015	1.195	0.047***	2.820	0.059	0.000	-0.036	0.054***	2.647	0.047
Italy	0.023*	1.863	0.022*	1.683	0.044	0.007	0.632	0.021	1.017	0.012
Japan	-0.004	-0.232	0.023	1.056	-0.008	-0.001	-0.062	0.023	1.379	0.009
Switzerland	0.014	1.030	0.046**	2.228	0.040	0.002	0.150	0.028*	1.688	0.022
U.K.	0.029***	3.277	0.026*	1.828	0.090	-0.005	-0.635	0.027**	2.410	0.020
Panel B. Semi-Annual Data										
Canada	-0.004	-0.351	-0.014	-0.761	-0.012	-0.012	-1.662	0.002	0.091	0.023
France	0.051**	2.252	0.121***	3.203	0.217	0.016	0.775	0.118***	3.096	0.162
Germany	0.028	1.244	0.147***	4.075	0.214	0.011	0.525	0.142***	3.477	0.199
Italy	0.046*	1.989	0.091***	2.928	0.149	0.012	0.626	0.091**	2.392	0.096
Japan	-0.015	-0.548	0.108***	3.224	0.068	0.022	0.817	0.071	1.451	0.075
Switzerland	0.024	0.937	0.146***	3.705	0.191	0.010	0.413	0.142***	2.819	0.180
U.K.	0.045**	2.387	0.087***	3.051	0.152	-0.001	-0.059	0.106***	2.744	0.093
Panel C. Annual Data										
Canada	-0.009	-0.568	-0.032	-1.016	0.007	-0.012	-1.015	-0.015	-0.449	0.021
France	0.085**	2.314	0.155***	3.411	0.308	-0.023	-0.697	0.228***	3.520	0.209
Germany	0.022	0.612	0.209***	4.165	0.297	-0.037	-1.124	0.282***	4.361	0.317
Italy	0.074*	1.812	0.105**	2.228	0.132	-0.007	-0.179	0.145*	1.948	0.052
Japan	-0.036	-0.823	0.143**	2.325	0.064	-0.009	-0.182	0.145	1.226	0.046
Switzerland	0.023	0.525	0.206***	3.045	0.223	-0.052	-1.352	0.305***	3.658	0.262
U.K.	0.089**	2.587	0.091*	1.717	0.145	-0.015	-0.402	0.151	1.694	0.036

Note: See notes in Tables 4 to 6.

Table 8 Forecasting Changes in Exchange Rates using Log Average Firm-Level Idiosyncratic Volatility: Subsamples

Country	1973-1985			1986-1998		
	LFIRM	t-value	ARSQ	LFIRM	t-value	ARSQ
Panel A. Quarterly Data						
Canada	-0.011	-1.559	0.016	-0.004	-0.270	-0.017
France	0.044*	2.000	0.042	0.062**	2.436	0.060
Germany	0.049**	2.122	0.048	0.062**	2.379	0.051
Italy	0.032*	1.896	0.023	0.040	1.670	0.012
Japan	0.037*	1.698	0.030	-0.004	-0.102	-0.020
Switzerland	0.045	1.560	0.026	0.064**	2.259	0.040
U.K.	0.053**	2.688	0.104	0.016	0.606	-0.014
Panel B. Semi-Annual Data						
Canada	-0.017	-1.105	-0.010	-0.010	-0.280	-0.032
France	0.130**	2.182	0.132	0.170***	3.572	0.238
Germany	0.146**	2.792	0.180	0.181***	3.556	0.229
Italy	0.089**	2.162	0.096	0.156***	3.807	0.150
Japan	0.113***	2.906	0.153	0.088	1.578	0.008
Switzerland	0.140**	2.535	0.152	0.180***	3.492	0.215
U.K.	0.113***	2.904	0.160	0.101*	2.026	0.054
Panel C. Annual Data						
Canada	-0.038	-1.789	0.097	-0.028	-0.529	-0.056
France	0.202**	2.308	0.201	0.190***	4.402	0.285
Germany	0.237***	3.386	0.343	0.200***	3.830	0.236
Italy	0.147*	2.193	0.132	0.142**	3.052	0.053
Japan	0.193***	3.241	0.207	0.056	0.674	-0.067
Switzerland	0.190*	2.062	0.159	0.245***	3.341	0.278
U.K.	0.200**	3.095	0.188	0.050	0.727	-0.068

Notes: See notes in Tables 4 to 6.

Table 9 Forecasting Changes in Exchange Rates of OECD Countries Using Full Sample

Country	DEF	t-value	ARSQ	LFIRM	t-value	ARSQ	DEF	t-value	LFIRM	t-value	ARSQ
Panel A Quarterly Data											
Australia	0.005	0.514	-0.006	0.008	0.696	-0.003	0.005	0.500	0.008	0.683	-0.009
Austria	0.021*	1.780	0.018	0.048***	2.903	0.047	0.015	1.208	0.042**	2.583	0.050
Belgium	0.031**	2.283	0.046	0.054***	3.140	0.060	0.024*	1.755	0.045***	2.707	0.082
Canada	-0.004	-0.829	-0.003	-0.003	-0.520	-0.005	-0.004	-0.810	-0.003	-0.511	-0.008
Denmark	0.021*	1.725	0.016	0.026***	2.666	0.029	0.020*	1.678	0.025**	2.605	0.044
Greece	0.032***	2.661	0.075	0.024**	2.139	0.026	0.031**	2.585	0.022**	2.117	0.097
Finland	0.024***	2.747	0.041	0.028**	2.049	0.019	0.021**	2.307	0.020	1.460	0.045
Iceland	0.073***	4.973	0.181	0.010	0.844	-0.004	0.072***	5.008	0.009	0.682	0.177
Ireland	0.030***	2.711	0.056	0.047***	3.096	0.055	0.024**	2.189	0.037**	2.593	0.086
Japan	-0.003	-0.217	-0.008	0.022**	2.007	0.017	-0.004	-0.251	0.022**	2.015	0.010
Luxembourg	0.031**	2.283	0.046	0.054***	3.140	0.060	0.024*	1.755	0.045***	2.707	0.082
Netherlands	0.024**	1.993	0.024	0.051***	3.097	0.054	0.017	1.406	0.044***	2.753	0.061
New Zealand	0.021*	1.794	0.018	0.013	1.082	0.001	0.021*	1.781	0.012	1.012	0.019
Norway	0.016*	1.663	0.011	0.016*	1.905	0.010	0.016	1.633	0.015*	1.829	0.020
Portugal	0.041***	3.645	0.100	0.021	1.183	0.002	0.040***	3.570	0.005	0.290	0.092
Spain	0.037***	4.107	0.089	0.039**	1.993	0.037	0.032***	3.581	0.027	1.373	0.101
Sweden	0.023**	2.030	0.026	0.019**	2.023	0.015	0.023**	2.040	0.019*	1.919	0.041
Switzerland	0.016	1.259	0.003	0.030**	2.569	0.029	0.015	1.209	0.029**	2.566	0.032
U.K.	0.030***	3.300	0.060	0.021***	2.826	0.026	0.029***	3.321	0.021***	2.743	0.085
Panel B Semi-Annual Data											
Australia	0.010	0.593	-0.012	0.002*	0.081	-0.016	0.010	0.595	0.002	0.080	-0.029
Austria	0.049**	2.122	0.043	0.145***	4.009	0.195	0.029	1.311	0.134***	3.736	0.199
Belgium	0.068**	2.688	0.089	0.156***	4.140	0.205	0.047*	1.944	0.138***	3.756	0.240
Canada	-0.009	-0.786	-0.005	-0.013	-1.270	0.008	-0.009	-0.763	-0.013	-1.302	0.003
Denmark	0.046**	2.024	0.038	0.065***	3.469	0.088	0.046**	2.123	0.065***	3.492	0.129
Greece	0.067***	3.256	0.148	0.062***	2.975	0.084	0.065***	3.278	0.059***	3.373	0.226
Finland	0.042**	2.313	0.046	0.083***	2.860	0.079	0.032	1.643	0.071**	2.355	0.096
Iceland	0.146***	4.243	0.248	0.036	1.131	-0.001	0.146***	4.353	0.036	1.073	0.251
Ireland	0.066***	3.121	0.106	0.134***	4.144	0.185	0.048**	2.327	0.116***	3.674	0.234
Japan	-0.006	-0.230	-0.015	0.061***	2.973	0.066	-0.006	-0.243	0.061***	2.967	0.052
Luxembourg	0.068**	2.688	0.089	0.156***	4.140	0.205	0.047*	1.944	0.138***	3.756	0.240
Netherlands	0.051**	2.101	0.045	0.150***	4.107	0.200	0.030	1.305	0.138***	3.860	0.205
New Zealand	0.037*	1.744	0.026	0.023	1.366	0.000	0.037*	1.795	0.023	1.288	0.027
Norway	0.032	1.671	0.017	0.037**	2.099	0.027	0.032*	1.679	0.037**	2.053	0.044
Portugal	0.089***	3.582	0.172	0.082*	1.862	0.044	0.081***	3.478	0.051	1.268	0.179
Spain	0.075***	4.097	0.142	0.097**	2.409	0.086	0.064***	3.532	0.072*	1.846	0.181
Sweden	0.039*	1.947	0.027	0.044**	2.439	0.038	0.039*	1.987	0.044**	2.317	0.067
Switzerland	0.034	1.328	0.009	0.079***	3.502	0.117	0.034	1.380	0.079***	3.598	0.128
U.K.	0.049***	2.761	0.059	0.047***	2.850	0.048	0.049***	2.806	0.047***	2.991	0.109

Table 9 Forecasting Changes in Exchange Rates of OECD Countries Using Full Sample (Continued)

Country	DEF	t-value	ARSQ	LFIRM	t-value	ARSQ	DEF	t-value	LFIRM	t-value	ARSQ
					Panel C Annual Data						
Australia	0.025	0.744	-0.024	-0.007	-0.175	-0.034	0.025	0.738	-0.008	-0.184	-0.059
Austria	0.064	1.683	0.027	0.202***	4.417	0.289	0.027	0.730	0.191***	3.717	0.270
Belgium	0.098**	2.355	0.098	0.209***	4.184	0.265	0.063	1.471	0.184***	3.572	0.288
Canada	-0.019	-1.365	-0.010	-0.022	-0.919	0.000	-0.019	-1.225	-0.022	-0.947	-0.011
Denmark	0.060	1.524	0.018	0.095***	2.803	0.102	0.058	1.653	0.094***	2.845	0.121
Greece	0.114***	3.222	0.166	0.119***	3.605	0.172	0.085**	2.314	0.155***	3.411	0.308
Finland	0.075**	2.116	0.057	0.129**	2.786	0.099	0.054	1.396	0.108**	2.258	0.110
Iceland	0.219***	2.887	0.187	0.037	0.573	-0.028	0.218***	2.932	0.031	0.442	0.163
Ireland	0.107***	3.406	0.149	0.174***	3.646	0.204	0.079**	2.298	0.143***	3.134	0.272
Japan	-0.029	-0.651	-0.023	0.093**	2.371	0.092	-0.031	-0.764	0.093**	2.450	0.074
Luxembourg	0.098**	2.355	0.098	0.209***	4.184	0.265	0.063	1.471	0.184***	3.572	0.288
Netherlands	0.064	1.672	0.024	0.206***	4.618	0.288	0.026	0.716	0.195***	3.918	0.268
New Zealand	0.051	1.362	-0.001	0.062	1.597	0.016	0.050	1.447	0.060	1.569	0.013
Norway	0.044	1.192	0.004	0.050	1.559	0.016	0.043	1.226	0.049	1.517	0.018
Portugal	0.150***	3.699	0.256	0.082	1.192	0.001	0.146***	3.525	0.025	0.424	0.228
Spain	0.123***	3.355	0.163	0.141**	2.116	0.089	0.104**	2.679	0.100	1.707	0.190
Sweden	0.059	1.210	0.012	0.056*	1.747	0.009	0.058	1.233	0.054	1.600	0.019
Switzerland	0.042	1.109	-0.013	0.117***	2.862	0.137	0.039	1.154	0.116***	2.941	0.125
U.K.	0.089***	2.788	0.082	0.053	1.627	0.008	0.088***	2.822	0.051	1.596	0.090

Notes: The table reports the OLS estimation results of regressing changes in nominal exchange rates using U.S. financial variables. The sample spans the period 1973:Q1 to 1998:Q4 for euro area countries and 1973:Q1 to 2004:Q2 for non-euro area countries. We use quarterly data in panel A, non-overlapping semi-annual data in panel B and annual data in panel C. The White-corrected standard error is used to calculate the t-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. DEF is the yield spread between Baa- and Aaa-rated corporate bonds and LFIRM is log average firm-level idiosyncratic volatility.

Table 10 Out-of-Sample Forecast Using Semi-Annual Data: 1973-1998

	MSE_A / MSE_B	ENC-NEW Statistic	ENC-NEW BS CV	MSE-F Statistic	MSE-F BS CV
Panel A. DEF					
Canada	1.060	-0.880	2.575	-1.935	1.314
France	0.938	3.962	2.495	2.232	1.296
Germany	1.026	1.469	2.466	-0.874	1.286
Italy	0.987	2.532	2.552	0.452	1.277
Japan	1.034	-0.489	2.485	-1.133	1.370
Switzerland	1.028	1.358	2.537	-0.940	1.392
U.K.	0.973	2.835	2.566	0.936	1.371
Panel B. LFIRM					
Canada	1.056	-0.455	2.320	-1.809	1.512
France	0.796	6.199	2.423	8.704	1.523
Germany	0.771	7.474	2.377	10.117	1.538
Italy	0.861	3.922	2.453	5.473	1.608
Japan	0.938	2.281	2.387	2.267	1.540
Switzerland	0.779	7.038	2.352	9.628	1.589
U.K.	0.900	3.480	2.322	3.765	1.568
Panel C. DEF and LFIRM					
Canada	1.125	-1.376	3.563	-3.783	1.184
France	0.789	7.163	3.482	9.085	1.164
Germany	0.811	6.443	3.494	7.920	1.253
Italy	0.894	3.995	3.475	4.050	1.277
Japan	0.976	1.913	3.521	0.852	1.207
Switzerland	0.831	5.790	3.524	6.924	1.258
U.K.	0.888	4.344	3.510	4.274	1.182

Notes: the table reports the out-of-sample forecasting results for changes in nominal exchange rates using non-overlapping semi-annual data. 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 to that of the random walk benchmark. 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 subsection V.C for more details. DEF is the yield spread between Baa- and Aaa-rated corporate bonds and LFIRM is log average firm-level idiosyncratic volatility. We use DEF, LFIRM, and both DEF and LFIRM as predictor(s) in panels A, B, and C, respectively.

Table 11 Out-of-Sample Forecast Using Semi-Annual Data: 1973-2003

		ENC-NEW		MSE-F	
	MSE_A / MSE_B	Statistic	BS. CV	Statistic	BS. CV
Panel A. DEF					
Canada	1.024	-0.454	2.725	-1.037	1.151
Japan	1.028	-0.520	2.844	-1.212	1.212
Switzerland	1.046	1.086	2.837	-1.922	1.316
U.K.	1.002	2.830	2.699	-0.103	1.189
Panel B. LIV					
Canada	1.035	0.126	2.589	-1.489	1.266
Japan	0.960	3.949	2.616	1.819	1.298
Switzerland	0.897	10.864	2.631	5.076	1.283
U.K.	0.995	4.649	2.599	0.217	1.284
Panel C. DEF and LIV					
Canada	1.059	-0.417	3.885	-2.458	0.756
Japan	1.002	3.468	3.833	-0.094	0.755
Switzerland	0.922	9.238	3.863	3.747	0.733
U.K.	0.954	5.163	3.817	2.121	0.738

Notes: See notes of Table 10.

Table 12: Data-Mining Bootstrap Critical Values for Semi-Annual Data: 1973-1998

Country	T-Statistics			ENC-NEW			MSE-F		
	10%	5%	1%	10%	5%	1%	10%	5%	1%
Canada	2.391	2.779	3.673	4.163	5.396	8.569	3.296	4.616	7.693
France	2.563	2.925	3.627	4.141	5.421	8.518	3.222	4.414	7.253
Germany	2.550	2.834	3.781	4.090	5.502	8.691	3.178	4.371	7.525
Italy	2.526	2.880	3.660	4.128	5.530	8.309	3.220	4.516	7.470
Japan	2.458	2.870	3.806	4.180	5.462	8.400	3.202	4.473	7.627
Switzerland	2.573	2.952	3.847	4.266	5.477	8.921	3.383	4.587	7.873
U.K.	2.528	2.895	3.602	4.058	5.361	8.599	3.147	4.385	7.401

Note: The table reports the critical values for t-statistics, the ENC-NEW test and the MSE-F test statistics obtained from a bootstrap procedure, in which we explicitly account for data mining. See subsection VI.D for details.

Table 13 Forecasting Exchange Rates Using Country-Specific Log Firm-Level Idiosyncratic Volatility

	LFIRM_L	t-value	LFIRM_US	t-value	ARSQ
Panel A Quarterly Data					
Canada	-0.004	-0.489	0.000	0.036	-0.012
France	-0.023	-1.310	0.055***	2.937	0.044
Germany	-0.029*	-1.957	0.073***	2.936	0.069
Italy	0.015	1.169	0.026*	1.920	0.026
Japan	-0.020	-1.351	0.031**	2.187	0.020
U.K.	0.002	0.099	0.019	0.890	0.018
Panel B Semi-Annual Data					
	LFIRM_L	t-value	LFIRM_US	t-value	ARSQ
Canada	-0.005	-0.293	-0.009	-0.606	-0.007
France	-0.057*	-1.694	0.158***	3.742	0.166
Germany	-0.070**	-2.872	0.206***	4.540	0.256
Italy	0.026	0.840	0.102***	3.426	0.110
Japan	-0.032	-1.119	0.076***	2.817	0.058
U.K.	-0.037	-0.865	0.080*	1.910	0.044
Panel C Annual Data					
	LFIRM_L	t-value	LFIRM_US	t-value	ARSQ
Canada	-0.004	-0.167	-0.021	-0.910	-0.034
France	-0.043	-0.325	0.209**	2.515	0.185
Germany	-0.116***	-3.370	0.320***	5.635	0.395
Italy	0.135***	3.345	0.137***	3.066	0.271
Japan	-0.148***	-3.107	0.178***	3.649	0.263
U.K.	-0.074	-1.016	0.120	1.612	-0.004

Note: The table reports the OLS regression results of forecasting changes in nominal exchange rates using both U.S. (LFIRM_US) and country-specific (LFIRM_L) log average firm-level idiosyncratic volatility. The sample spans the period 1973 to 1998 for euro area countries and the period 1973 to 2003 for non-euro area countries. The White-corrected standard error is used to calculate the t-value. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. We use quarterly data in panel A, non-overlapping semi-annual data in panel B, and annual data in panel C.