NORTHERN ARIZONA UNIVERSITY
The W. A. Franke College of Business

Foreign Exchange Volatility and Stock Returns

Working Paper Series—12-05 | October 2012

Ding Du
Northern Arizona University
The W. A. Franke College of Business
PO Box 15066
Flagstaff, AZ 86011.5066

Ding.Du@nau.edu

(928) 523-7274
Fax: (928) 523-7331

Ou Hu
Department of Economics
Youngstown State University
Youngstown, OH 44555

ohu@ysu.edu
(330) 941-2061

Foreign Exchange Volatility and Stock Returns

1. Introduction

The International Capital Asset Pricing Model of Solnik (1974), Sercu (1980), and Adler and Dumas (1983) suggests that the covariance of stock returns with foreign exchange changes should be a priced factor when purchasing power parity is violated. Motivated by this insight, empirical studies on foreign exchange risk typically add foreign exchange changes to the standard asset-pricing models as an additional factor. However, this approach usually finds that only low proportions of U.S. stocks have significant foreign exchange exposure and foreign exchange risk is not priced.[1]

Recently, Menkhoff, Sarno, Schmeling, and Schrimpf (2011) (MSSS) find that

(G)lobal FX volatility is a key driver of risk premia in the cross-section of carry trade returns. The pricing power of volatility also applies to other cross-sections, such as a common FX momentum strategy, individual currencies' excess returns, domestic U.S. corporate bonds, U.S. equity momentum, as well as FX option portfolios and international bond portfolios. (p. 3)

Although MSSS focus on understanding carry trade returns in foreign exchange markets, the pervasiveness of the pricing power of foreign exchange volatility across such a variety of test assets (documented in their study) suggests a potentially promising approach to understanding foreign exchange risk in the equity market. That is, it may be foreign exchange volatility (second moments) not foreign exchange changes (first moments) that matter for the cross-section of stock returns. This perspective also has a number of theoretical justifications. First, as MSSS argue, volatility can be a state variable in the Merton (1973) sense. Second, Shapiro (1974), Dumas (1978), and Levi (1990) among others suggest that foreign exchange changes can affect firms' cash flows, which implies that foreign exchange volatility can influence firms' cash flow volatility and, therefore, the discount rate. Motivated by the above observations, we study whether foreign exchange volatility is a priced factor in the US stock market in this paper.

If foreign exchange volatility is a priced factor in the stock market, it should help reduce pricing errors of standard asset-pricing models, such as the CAPM of Sharpe (1964) and Lintner (1965) and the four-factor model of Carhart (1997).[2] Therefore, we focus on the comparison between the performance of the standard models and that of their enhanced versions with foreign exchange volatility as an additional factor.

Empirically, we use a wide variety of test assets commonly used in international finance and empirical asset pricing, including 25 size and BM portfolios, 25 size and momentum portfolios, 10 portfolios formed on earnings-to-price, 10 portfolios formed on dividend yield, 10 portfolios formed on short-term reversal, 10 portfolios formed on long-term reversal, and 30 industry portfolios. In terms of empirical methodology, we employ the cross-sectional regression methodology of Fama and MacBeth (1973) as well as the time-series regression approach of Fama and French (1996). For robustness, we also use the mimicking portfolio approach of Fama and French (1993).

Our findings can be easily summarized: empirically, foreign exchange volatility has no power in explaining either the time-series or the cross-section of stock returns. Our findings call

[1] See also Jorion (1990, 1991), Khoo (1994), Bartov and Bodnar (1994), Allayannis (1997), Chow, Lee and Solt (1997), Vassalou (2000), Bodnar and Wong (2003), Bartram (2004), Bartram and Bodnar (2005), Martin and Mauer (2005), Bartram (2007), Bartram (2008), Francis, Hasan, and Hunter (2008), Kolari, Moorman, and Sorescu (2008), Bartram, Brown, and Minton (2010), Du and Hu (2012), and Antell and Vaihekoski (2012).

[2] The four factor model augments the three-factor model of Fama and French (1993) with a momentum factor, since the three-factor model is well-known to be unable to account for stock momentum of Jegadeesh and Titman (1993) (e.g. Fama and French, 1996).

for more research on foreign exchange risk. In theory, foreign exchange volatility can affect firms' cash flow volatility. Therefore, it should be a priced factor for equity returns. Bartov, Bodnar, and Kaul (1996) and Adrian and Rosenberg (2008) imply that it might be the long-term component of foreign exchange volatility that affects systematic risk of firms. Therefore, future research may decompose foreign exchange volatility into different components and examine their differential effects on the time-series and the cross-section of stock returns.

The remainder of the paper is organized as follows: Section 2 describes the data. Section 3 presents empirical methodology. Section 4 reports empirical results when foreign exchange volatility innovations are measured by the first difference of foreign exchange volatility. Section 5 presents the results when foreign exchange volatility innovations are measured by factor-mimicking portfolio returns. Section 6 concludes the manuscript.

2. Data

Our full sample includes 34 countries whose daily exchange rate data are available from the Federal Reserve Bank of St. Louis. They are Austria, Australia, Belgium, Brazil, Canada, China, Denmark, Euro Area, Finland, France, Germany, Greece, Hong Kong, India, Ireland, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Portugal, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Venezuela, and United Kingdom. Our sample period is from January 1973 to December 2010. The start of our sample period coincides with the start of fluctuating exchange rates (see Bartov, Bodnar, and Kaul, 1996). Monthly data of relevant factors including the risk-free rate (RF), the excess market return (MKT), the momentum factor (WML), the size factor (SMB), and the book-to-market-equity factor (HML) are from Kenneth French's website.[3]

We follow MSSS to construct the foreign exchange (FX) volatility series. Specifically, we first compute the absolute daily log return for each currency on each day in our sample. We then average over all currencies available on any given day. Finally, we average daily values within a given month to obtain the monthly FX volatility.

We measure FX volatility innovations in two ways. The first way is to take the first difference of the FX volatility as in Ang, Hodrick, Xing, and Zhang (2006).[4] The second way is to construct a factor- mimicking portfolio along the same line as Fama and French (1993). For two reasons, this second approach, in principle, should be more powerful than the first one. First, FX volatility changes are a macroeconomic variable (not returns), which may contain information that is irrelevant to asset pricing (and may also have measurement errors). In contrast, a factor-mimicking portfolio in principle captures only the information in FX volatility innovations that is pertinent to stock returns, and therefore should reduce the noise in estimations.[5] Second, to construct our factor-mimicking portfolio, we estimate firms' FX volatility sensitivities in a rolling regression fashion, which allows time variation in volatility sensitivity in a non-structural framework.[6] Panel A of Figure 1 shows the time series of the FX volatility; Panel B presents the FX volatility innovations as the first difference; Panel C depicts the innovations as the factor-mimicking portfolio return. Table 1 presents the descriptive statistics for the FX volatility and its innovations.

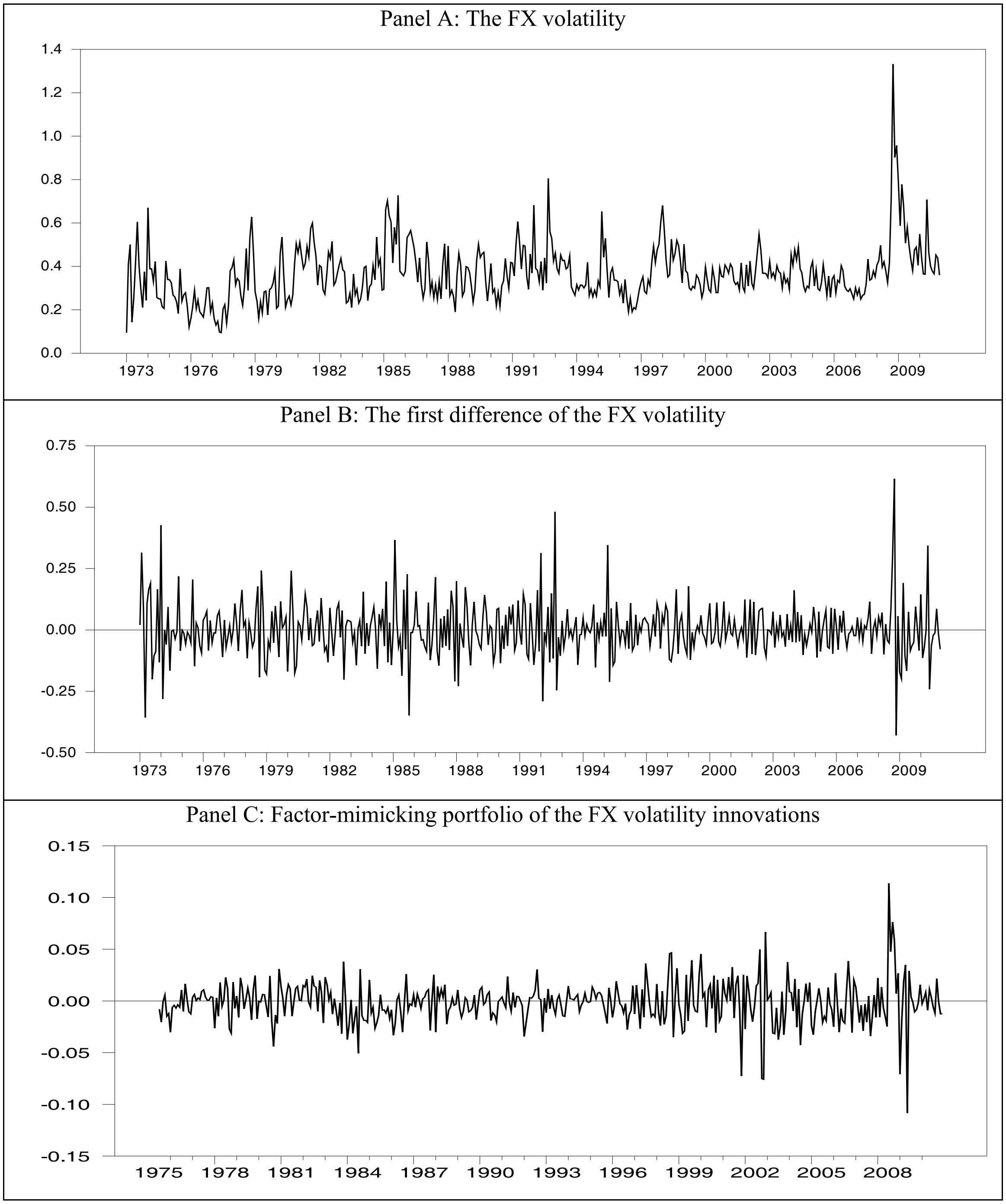
[3] We thank Fama and French for making these data available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[4] Using the AR(1) residuals as in MSSS yields qualitatively similar results. However, as MSSS point out, this approach not only may introduce an errors-in-variables problem but also requires estimation on the full sample which is not implementable (since market participants do not have such information in real time).

[5] See Chan, Karceski and Lakonishok (1998 and 1999) for more discussion and applications of the mimicking portfolio approach.

[6] See Doidge, Griffin, and Williamson (2006) for more discussion.

Figure 1 Foreign exchange volatility: 1973-2010



Panel A of Figure 1 shows the time series of the FX volatility; Panel B presents the FX volatility innovations as the first difference; Panel C depicts the innovations as the factor-mimicking portfolio return.

Table 1: Descriptive statistics of the FX volatility and its innovations

	Mean	Std Error	Minimum	Maximum
FX volatility	0.3539	0.1400	0.0258	1.3318
First difference of the FX volatility	0.0007	0.1086	-0.4299	0.6155
Factor-mimicking portfolio of the FX volatility innovations	-0.0014	0.0192	-0.1083	0.1137

Table 1 presents the descriptive statistics for the FX volatility and its innovations.

When FX volatility innovations are measured by the first difference of the FX volatility, we focus on 25 size and book-to-market (BM) portfolios (which are commonly used in the literature) as our test assets. For robustness, besides 25 size and book-to-market (BM) portfolios, we expand our set of test assets to include 25 size and momentum portfolios, 10 portfolios formed on earnings-to-price, 10 portfolios formed on dividend yield, 10 portfolios formed on short-term reversal, 10 portfolios formed on long-term reversal, and 30 industry portfolios.[7]

When FX volatility innovations are measured by factor-mimicking portfolio returns, in line with Fama and French (1993), we construct 25 size and volatility-sensitivity portfolios as our testing assets. Using such volatility-sensitivity portfolios can maximize the power of the tests, because these portfolios are formed on the sensitivity to FX volatility innovations.

3. Empirical methodology

To examine whether the FX volatility has marginal power to explain the time-series and cross-section of stock returns, we focus on the comparison between the performance of two standard asset-pricing models and that of their enhanced versions with the FX volatility as an additional factor. The first standard model is the CAPM of Sharpe (1964) and Lintner (1965) (MKT):

$$r_{it} = \alpha_i + b_i MKT_t + \varepsilon_{it} \tag{1}$$

where r_{it} is the excess return on asset *i* in period *t*, and MKT_t is the excess market return. If foreign exchange volatility is a priced factor, it should reduce pricing errors of the CAPM. Thus, we consider an enhanced version of the CAPM, a two-factor model, which augments the CAPM with an FX volatility factor (MKT+VOL):

$$r_{it} = \alpha_i + b_i MKT_t + c_i VOL_t + \varepsilon_{it} \tag{2}$$

where VOL_t is the volatility innovations measured by either the first difference of the FX volatility or the factor-mimicking portfolio return.

It is well known that the CAPM fails to capture the size, value and momentum effects (e.g. Fama and French, 1993; Jegadeesh and Titman, 1993). Therefore, the second standard model we consider is the four-factor model of Carhart (1997) (MKT+SMB+HML+WML), which enhances the CAPM with the size, value and momentum factors:

$$r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + \varepsilon_{it} \tag{3}$$

[7] All the monthly portfolio return data are from Kenneth French's website. The details of the construction of these portfolios are also available at Kenneth French's website.

where SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks, and WML_t is the difference between the month t returns on diversified portfolios of the winners and losers of the past year. Again, if foreign exchange volatility is a priced factor, it should reduce pricing errors of this model. Thus, we also consider an enhanced version of this model, a five-factor model (MKT+SMB+HML+WML+VOL) with the FX volatility as an additional factor.

$$r_{it} = \alpha_i + b_i MKT_t + s_i SMB_t + v_i HML_t + m_i WML_t + c_i VOL_t + \varepsilon_{it} \qquad (4)$$

To evaluate the performance of these asset-pricing models, we carry out two complementary sets of tests. The first set focuses on the time-series of stock returns with the time-series regression approach of Fama and French (1993, 1996). Essentially, Eqs. (1) through (4) are estimated for each test asset with monthly data. Following relevant literature (e.g. Fama and French, 2011), we evaluate each model based on the magnitude of pricing errors (the average absolute value of the intercepts and the average of the standard errors of the intercepts), the explanatory power (the average adjusted R^2), and the Gibbons, Ross, and Shanken (1989) (GRS) F-test statistic for the hypothesis that the intercepts are jointly equal to zero for all test assets.

The second set of tests concentrates on the cross-section of stock returns with the Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) two-pass methodology – estimating factor loadings in the first pass, and using those to obtain risk premiums in the second pass – with standard refinements: the Shanken (1992) correction to obtain errors-in-variables (EIV) robust standard errors, accounting for the fact that factor sensitivities are estimated, and the Shanken and Zhou (2007) correction to generate misspecification (MIS) robust standard errors. We also take into consideration the suggestions of Lewellen, Nagel and Shanken (2010) regarding cross-sectional asset-pricing tests: (1) we expand the set of test assets beyond portfolios formed on size and BM; (2) we report not only the OLS results but also the GLS results. We evaluate each model based on the adjusted R^2 (i.e. the pricing error).

4. FX volatility innovation as the first difference of the FX volatility

4.1 Main results

Panel A of Table 2 summarizes time-series regressions to explain monthly excess returns on 25 size-BM portfolios. Panel A shows the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R^2 (R^2), and the GRS F-test statistic (GRS).

We focus on the comparison between the standard models and their enhanced versions with the FX volatility as an additional factor. First, we examine the CAPM (Eq. 1) and its enhanced version (Eq. 2). As we can see, enhancing the CAPM with the FX volatility does not improve the performance of the CAPM at all. From the CAPM to its enhanced version, the average absolute value of the intercepts, the average adjusted R^2, and the GRS statistics all stay the same. Thus, disappointingly, the time-series evidence based on the CAPM suggests that the FX volatility is not priced.

Table 2:
Summary statistics of time-series and cross-sectional regressions for 25 size-BM portfolios: 1973-2010

Panel A: Summary statistics of time-series regressions

Model	$\lvert\alpha\rvert$	$S(\alpha)$	R^2	GRS
MKT	0.31	0.16	0.74	3.95*
MKT+VOL	0.31	0.16	0.74	3.95*
MKT+SMB+HML+WML	0.10	0.08	0.91	2.64*
MKT+SMB+HML+WML+VOL	0.10	0.08	0.91	2.64*

Panel B: Two-pass OLS cross-sectional regressions

Model	Factor	γ	t_{EIV}	t_{MIS}	R^2
MKT	Alpha	1.38*	3.03	2.96	0.13
	MKT	-0.65	-1.29	-1.26	
MKT+VOL	Alpha	1.59*	3.56	3.24	0.17
	MKT	-0.86	-1.77	-1.59	
	VOL	0.06	1.61	0.94	
MKT+SMB+HML+WML	Alpha	0.69	1.68	1.02	0.71
	MKT	-0.18	-0.38	-0.25	
	SMB	0.20	1.32	1.31	
	HML	0.47*	3.15	3.15	
	WML	2.03	2.17	0.96	
	Alpha	0.73	1.73	1.11	0.71
MKT+SMB+HML+WML+VOL	MKT	-0.23	-0.47	-0.32	
	SMB	0.22	1.46	1.41	
	HML	0.47*	3.13	3.14	
	WML	2.39	2.37	1.06	
	VOL	-0.02	-0.98	-0.61	

Panel A summarizes time-series regressions to explain monthly excess returns on 25 size-BM portfolios. Panel A shows the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R^2 (R^2), and the GRS F-test statistic (GRS). Panel B reports the Fama and MacBeth (1973) two-pass OLS regressions (with a constant) with 25 size-BM portfolios as the test assets. γ is the estimated risk premium associated with each factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R^2. The asterisk indicates the significance at the 5% level.

Next, we compare the four-factor model of Carhart (1997) (Eq. 3) with its enhanced version (Eq. 4).[8] It is evident that augmenting the four-factor model with the FX volatility does not improve the performance of the model. From the four-factor model to its enhanced version, the average absolute value of the intercepts, the average adjusted R^2, and the GRS statistics all stay the same. Thus, the time-series evidence based on the four-factor model does not support the notion that the FX volatility is priced either.

Panel B of Table 1 reports the Fama and MacBeth (1973) two-pass OLS regressions with 25 size-BM portfolios as the test assets. γ is the estimated risk premium associated with each

[8] The four-factor model performs noticeably better than the CAPM. From the CAPM to the four-factor model, the average absolute value of the intercepts decreases from 0.31 to 0.10; the average adjusted R^2 increases from 0.74 to 0.91; and the GRS statistics reduces from 3.95 to 2.64. Our results are in general consistent with previous studies (e.g. Fama and French, 2011).

Table 3 Sub-sample results for 25 size-BM portfolios

Panel A: Summary statistics of time-series regressions

	1973:1 – 1985:9				1985:10 – 2010:12			
Model	$\lvert\alpha\rvert$	S(α)	R^2	GRS	$\lvert\alpha\rvert$	S(α)	R^2	GRS
MKT	0.48	0.20	0.78	1.46	0.25	0.21	0.72	4.60*
MKT+VOL	0.49	0.20	0.78	1.49	0.25	0.21	0.72	4.64*
MKT+SMB+HML+WML	0.10	0.12	0.93	0.93	0.13	0.10	0.90	3.84*
MKT+SMB+HML+WML+VOL	0.10	0.12	0.93	0.90	0.13	0.10	0.90	3.87*

Panel B: Two-pass OLS cross-sectional regressions

		1973:1 – 1985:9				1985:10 – 2010:12			
Model	Factor	γ	t_{EIV}	t_{MIS}	R^2	γ	t_{EIV}	t_{MIS}	R^2
MKT	Alpha	0.90	1.86	1.68	-0.02	1.60*	2.46	2.43	0.26
	MKT	-0.29	-0.47	-0.45		-0.82	-1.16	-1.15	
MKT+VOL	Alpha	0.89	2.00	0.73	-0.07	1.62*	2.61	2.57	0.23
	MKT	-0.28	-0.47	-0.24		-0.85	-1.27	-1.24	
	VOL	0.00	-0.04	-0.01		0.01	0.33	0.25	
MKT+SMB+HML+WML	Alpha	0.46	0.98	0.89	0.89	0.29	0.41	0.40	0.59
	MKT	-0.32	-0.51	-0.48		0.41	0.52	0.51	
	SMB	0.48*	1.96	1.96		0.08	0.40	0.40	
	HML	0.76*	3.13	3.12		0.31	1.63	1.63	
	WML	-0.25	-0.36	-0.33		3.79*	3.17	2.84	
MKT+SMB+HML+WML+VOL	Alpha	0.41	0.90	0.81	0.89	0.46	0.65	0.61	0.64
	MKT	-0.25	-0.42	-0.39		0.21	0.27	0.26	
	SMB	0.46	1.90	1.89		0.11	0.56	0.56	
	HML	0.77*	3.14	3.13		0.32	1.64	1.65	
	WML	-0.25	-0.36	-0.33		3.89*	3.04	2.84	
	VOL	0.01	0.48	0.40		-0.05	-1.69	-1.48	

Panel A summarizes time-series regressions to explain monthly excess returns on 25 size-BM portfolios. Panel A shows the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R2 (R2), and the GRS F-test statistic (GRS). Panel B reports the Fama and MacBeth (1973) two-pass OLS regressions (with a constant) with 25 size-BM portfolios as the test assets. γ is the estimated risk premium associated with each factor. tEIV and tMIS are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R2. The asterisk indicates the significance at the 5% level.

factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R^2.

From the CAPM to its enhanced version, the intercept (Alpha) increases slightly from 1.38 to 1.59 (both are significant at the 5% level based on either t_{EIV} or t_{MIS}); and the cross-sectional R^2 increases insignificantly from 0.13 to 0.17.[9] From the four-factor model of Carhart (1997) to its augmented version, the intercept (Alpha) increases from 0.69 to 0.73 (both are not significant at the 5% level based on either t_{EIV} or t_{MIS}); and the cross-sectional R^2 stays the same at

[9] Lewellen, Nagel and Shanken (2010) show that "a sample adjusted R^2 might need to be as high as 44% to be statistically significant in models with one factor, 62% in models with three factors, and 69% in models with five factors." (p. 176)

0.71. Furthermore, the FX volatility factor is never significant. Taken together, consistent with the time-series regression results, the cross-sectional regression results also suggest that the FX volatility is not priced.

4.2 Robustness check

4.2.1 Sub-sample results

Since there is evidence suggesting that foreign exchange exposure and risk premium can be time varying,[10] for robustness, we examine two sub-sample periods. One is from 1973:1 to 1985:9, and the other is from 1985:10 to 2010:12. This division of the sample is based on the consideration of the Plaza Accord in 1985:9. The sub-sample results are reported in Table 3 in the same fashion as Table 2. As we can see, for both sub-sample periods, adding the FX volatility to the standard models such as the CAPM and the four-factor model of Carhart (1997) does not reduce pricing errors in time series and cross-sectional regressions. Furthermore, the FX volatility does not have a significant risk premium in either period. Therefore, the sub-sample evidence confirms the whole-sample evidence, suggesting that the FX volatility is not priced.

4.2.2 Test results for the expanded set of test assets

To "relax the tight factor structure of size-B/M portfolios" (Lewellen, Nagel and Shanken 2010, p. 182), we expand our set of test assets to 120 portfolios formed on, besides size-BM, size-momentum, earnings-to-price, dividend yield, short-term reversal, long-term reversal, and industry. Tables 4 and 5 summarize time-series and cross-sectional regressions in the same fashion as Table 2.

In Table 4, we report summary time-series regression statistics for the portfolios formed on individual characteristics (i.e. earnings-to-price) as well as those for all 120 assets. Regardless of whether we look at the portfolios formed on individual characteristics or all 120 portfolios, the same pattern emerges: the enhanced versions of the standard models that include the FX volatility do not reduce the pricing errors or increase the explanatory power in time-series regressions. Consider the summary statistics for regressions with 120 portfolios as test assets, the average absolute values of the intercepts from 120 time-series regressions are 0.24 for the CAPM, 0.24 for its enhanced version, 0.12 for the four-factor model of Carhart (1997), and 0.12 for its augmented version. For these models, the average adjusted R^2s are 0.72, 0.72, 0.82 and 0.82; and the GRS statistics are 2.65, 2.66, 2.28 and 2.28, respectively.

Panel A of Table 5 reports the Fama and MacBeth (1973) two-pass OLS regressions with 120 portfolios as the test assets. The results are, in general, consistent with those in Table 2. The models that include the FX volatility do not outperform the standard models without this factor. For instance, the OLS R^2s are 0.01 for the CAPM, 0.02 for its enhanced version, 0.60 for the four-factor model of Carhart (1997), and 0.61 for its augmented version. Furthermore, the FX volatility factor is never significant. Thus, the evidence confirms that the FX volatility has no power to explain either the time-series or the cross-section of stock returns for a wide variety of test assets.

4.2.3 GLS regressions

Lewellen, Nagel and Shanken (2010) suggest researchers report not only the OLS results but also the GLS results, especially the GLS cross-sectional R^2. As they point out, "The broader point is that, while the OLS R^2 might be relevant for some questions—for example, asking whether a model's predictions of expected returns are accurate for a given set of assets (subject to the limitations discussed in Section 2)—the GLS R^2 is probably more relevant for other

[10] See for instance Francis, Hasan, and Hunter (2008).

Table 4 Summary statistics of time-series regressions for a variety of test assets, 1973-2010

Test assets	Model	|α|	S(α)	R^2	GRS
Size/Momentum	MKT	0.36	0.17	0.73	4.46*
	MKT+VOL	0.36	0.17	0.73	4.46*
	MKT+SMB+HML+WML	0.14	0.10	0.91	3.34*
	MKT+SMB+HML+WML+VOL	0.14	0.10	0.91	3.34*
Earnings/Price	MKT	0.22	0.12	0.81	2.18*
	MKT+VOL	0.22	0.12	0.81	2.19*
	MKT+SMB+HML+WML	0.06	0.08	0.87	0.76
	MKT+SMB+HML+WML+VOL	0.06	0.08	0.87	0.77
Dividend Yield	MKT	0.17	0.12	0.75	1.27
	MKT+VOL	0.17	0.12	0.75	1.25
	MKT+SMB+HML+WML	0.08	0.10	0.83	0.91
	MKT+SMB+HML+WML+VOL	0.08	0.10	0.83	0.88
Short-Term Reversal	MKT	0.13	0.10	0.85	1.51
	MKT+VOL	0.13	0.10	0.85	1.48
	MKT+SMB+HML+WML	0.14	0.11	0.86	1.37
	MKT+SMB+HML+WML+VOL	0.14	0.11	0.86	1.32
Long-Term Reversal	MKT	0.21	0.12	0.81	1.90*
	MKT+VOL	0.21	0.12	0.81	1.89*
	MKT+SMB+HML+WML	0.07	0.10	0.86	0.69
	MKT+SMB+HML+WML+VOL	0.07	0.10	0.86	0.66
Industry	MKT	0.16	0.21	0.58	1.04
	MKT+VOL	0.16	0.21	0.58	1.04
	MKT+SMB+HML+WML	0.17	0.18	0.63	1.69*
	MKT+SMB+HML+WML+VOL	0.17	0.18	0.63	1.68*
120 assets	MKT	0.24	0.16	0.72	2.65*
	MKT+VOL	0.24	0.16	0.72	2.66*
	MKT+SMB+HML+WML	0.12	0.11	0.82	2.28*
	MKT+SMB+HML+WML+VOL	0.12	0.11	0.82	2.28*

In Table 4, we report summary time-series regression statistics for the portfolios formed on individual characteristics (i.e. earnings-to-price) as well as those for all 120 assets. Table 4 shows the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R2 (R2), and the GRS F-test statistic (GRS). The asterisk indicates the significance at the 5% level.

questions—for example, asking how well a model explains the risk-return opportunities available in the market." (p. 184). We thus report the GLS results in Panel B of Table 5 for 120 portfolios over the same sample period from 1973 to 2010. The results are, in principle, consistent with the OLS results in Panel A. The models that include the FX volatility do not outperform the standard models without this factor. Furthermore, the FX volatility factor is never significant.

4.2.4 FX volatility innovations measured by the AR(1) residuals

MSSS use the AR(1) residuals of the FX volatility as FX volatility innovations. We thus repeat our tests with 120 portfolios as our test assets and the AR(1) residuals as innovations. Panel A of Table 6 summarizes the time-series and the OLS cross-sectional regressions results. We only report the results for the models with the FX volatility, since the results for the CAPM and the four-factor model of Carhart (1997) are not affected by the FX innovation measures and are the same as those in Table 4 (for 120 assets) and Table 5.

A comparison between Tables 4 and 5 and Panel A of Table 6 reveals that using AR(1) residuals produces almost identical results. For instance, for the enhanced CAPM, in time-series regressions, the average absolute value of the intercepts is 0.24 when the FX innovations are

Table 5 Two-pass cross-sectional regressions for 120 test assets, 1973-2010

Model	Factor	Panel A: OLS regressions				Panel B: GLS regressions			
		γ	t_{EIV}	t_{MIS}	R^2	γ	t_{EIV}	t_{MIS}	R^2
MKT	Alpha	0.82*	2.94	2.87	0.01	0.62*	5.21	3.56	-0.29
	MKT	-0.21	-0.59	-0.58		-0.14	-0.57	-0.51	
MKT+VOL	Alpha	0.80*	2.86	2.78	0.02	0.61*	5.01	3.43	-0.28
	MKT	-0.19	-0.52	-0.52		-0.13	-0.50	-0.45	
	VOL	-0.02	-0.83	-0.52		-0.02	-1.67	-0.94	
MKT+SMB+HML+WML	Alpha	0.45	1.71	1.67	0.60	0.53*	4.16	2.88	0.58
	MKT	0.08	0.23	0.23		-0.05	-0.21	-0.18	
	SMB	0.22	1.45	1.44		0.25	1.65	1.65	
	HML	0.34*	2.20	2.20		0.38*	2.58	2.57	
	WML	0.72*	3.20	3.19		0.72*	3.32	3.31	
MKT+SMB+HML+WML+VOL	Alpha	0.34	1.52	1.40	0.61	0.53*	4.10	2.84	0.56
	MKT	0.19	0.60	0.57		-0.05	-0.18	-0.16	
	SMB	0.22	1.41	1.41		0.25	1.66	1.66	
	HML	0.35*	2.30	2.29		0.38*	2.57	2.55	
	WML	0.74*	3.33	3.32		0.72*	3.31	3.30	
	VOL	0.02	0.79	0.69		-0.01	-1.28	-0.74	

Panel A reports the Fama and MacBeth (1973) two-pass OLS regressions with 120 portfolios as the test assets, where Panel B presents the GLS results. γ is the estimated risk premium associated with each factor. tEIV and tMIS are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS and GLS cross-sectional adjusted R2. The asterisk indicates the significance at the 5% level.

measured by the first difference, and 0.24 when innovations are measured by the AR(1) residuals. In OLS cross-sectional regressions, the adjusted R^2 is 0.02 in the first case and 0.08 in the second case. Again, the FX volatility factor is never significant.

4.2.5 Developed country currencies

We also follow MSSS and study a subsample which includes only the currencies of developed countries. These countries are Australia, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, Norway, Sweden, Switzerland, and the United Kingdom. The results for 120 portfolios are reported in Panel B of Table 6. Again, using developed country currencies yields almost identical results, suggesting that the FX volatility has no power in explaining either the time-series or the cross-section of stock returns.

5. FX volatility innovations as the factor-mimicking portfolio returns

As we point out, using factor-mimicking portfolio returns to measure FX volatility innovations and the portfolios formed on the volatility sensitivity as test assets can maximize the power of tests. Thus, in this section, we provide the details on how to construct the FX volatility mimicking portfolio and associated test assets. We also report the relevant test results.

5.1 Main results

In line with Fama and French (1993), we construct our factor-mimicking portfolio of the FX volatility in two steps. The first step is to form six value-weighted size and volatility-sensitivity portfolios with all the stocks in the Center for Research in Security Prices (CRSP). The portfolios, which are constructed at the end of each June, are the intersections of two portfolios formed on size (market capitalization) and three portfolios formed on volatility sensitivity. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. The

Table 6 Robustness check, 1973-2010

Panel A: Innovations measured as the AR(1) residuals

Summary statistics of time-series regressions

Model	|α|	S(α)	R^2	GRS
MKT+VOL	0.24	0.16	0.72	2.65*
MKT+SMB+HML+WML+VOL	0.12	0.11	0.82	2.26*

Two-pass OLS cross-sectional regressions

Model	Factor	γ	t_{EIV}	t_{MIS}	R^2
MKT+VOL	Alpha	0.76*	2.61	2.55	0.08
	MKT	-0.14	-0.39	-0.39	
	VOL	-0.03	-1.58	-1.17	
MKT+SMB+HML+WML+VOL	Alpha	0.36	1.64	1.49	0.61
	MKT	0.16	0.53	0.50	
	SMB	0.22	1.44	1.43	
	HML	0.35*	2.25	2.24	
	WML	0.74*	3.33	3.31	
	VOL	0.01	0.38	0.35	

Panel B: FX volatility based on developed country currencies

Summary statistics of time-series regressions

Model	|α|	S(α)	R^2	GRS
MKT+VOL	0.24	0.16	0.72	2.66*
MKT+SMB+HML+WML+VOL	0.12	0.11	0.82	2.28*

Two-pass OLS cross-sectional regressions

Model	Factor	γ	t_{EIV}	t_{MIS}	R^2
MKT+VOL	Alpha	0.82*	2.99	2.90	0.01
	MKT	-0.21	-0.59	-0.58	
	VOL	0.00	-0.14	-0.08	
MKT+SMB+HML+WML+VOL	Alpha	0.34	1.50	1.36	0.61
	MKT	0.19	0.60	0.57	
	SMB	0.22	1.42	1.41	
	HML	0.35*	2.30	2.29	
	WML	0.74*	3.30	3.29	
	VOL	0.02	0.90	0.74	

Panel A summarizes time-series and OLS cross-sectional regressions when the AR(1) residuals are employed as innovations. Panel B presents the corresponding results when only developed country currencies are used. The test assets are 120 portfolios. For time-series regressions, we report the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R2 (R2), and the GRS F-test statistic (GRS). For cross-sectional regressions, we present the Fama and MacBeth (1973) two-pass OLS regression results. γ is the estimated risk premium associated with each factor. tEIV and tMIS are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R2. The asterisk indicates the significance at the 5% level.

volatility sensitivity for June of year t is estimated with the prior two years' data based on the multi-factor model in Eq. (4).[11] The FX volatility is calculated with all the currencies in our sample. The volatility-sensitivity breakpoints are the 30th and 70th percentiles. These portfolios are held for one year (from July of year t to June of year t+1) and rebalanced at the end of June of

[11] As a result, our test period in this section is from 1975:7 to 2010:12.

year t+1. By rebalancing the portfolios on an annual basis in a conditional fashion, we allow firms' volatility sensitivity to be time varying.

The second step is to define the factor-mimicking portfolio returns as the average return on the two positive sensitivity portfolios minus the average return on the two negative sensitivity portfolios. That is, our FX volatility risk factor is

$$VOL_t = \left(\frac{BP_t + SP_t}{2} \right) - \left(\frac{BN_t + SN_t}{2} \right) \tag{6}$$

where BP_t, SP_t, BN_t and SN_t are the returns on large and positive sensitivity, small and positive sensitivity, large and negative sensitivity, and small and negative sensitivity portfolios, respectively.

Again, in line with Fama and French (1993), we construct 25 size and volatility-sensitivity portfolios as our testing assets. These 25 portfolios are constructed in a similar way as the six size and volatility-sensitivity portfolios. Table 7 summarizes the results of the time-series and the OLS cross-sectional regressions. As we can see, even if we use an approach that can maximize the power of tests, the FX volatility still has no power to explain the time-series or the cross-section of stock returns. In both time series and cross-sectional regressions, the models that include the FX volatility do not noticeably outperform the standard models that exclude this factor. Furthermore, the FX volatility factor is never significant in the cross-sectional tests. Thus, the evidence confirms that the FX volatility is not priced.

5.2 Robustness check

We perform a variety of robustness tests. The first one is to examine the two sub-sample periods, 1975:7 to 1985:9 and 1985:10 to 2010:12. The results are reported in Table 8. As we can see, for both sub-sample periods, adding the FX volatility to the standard models does not reduce pricing errors in time series and cross-sectional regressions. Furthermore, the FX volatility does not have a significant risk premium in either period. Therefore, the sub-sample evidence confirms the whole-sample evidence, suggesting that the FX volatility is not priced.

The second robustness test is to use the developed country currencies to construct the FX volatility mimicking portfolio and associated size and volatility-sensitivity portfolios. The results are reported in Table 9. As we can see, the results are qualitatively similar as those in Table 7 based on all the currencies. In both time series and cross-sectional regressions, the models with the FX volatility do not outperform the standard models without this factor. Furthermore, the FX volatility factor is never significant in the cross-sectional tests.

We also undertake a number of other experiments, including dropping the stocks with a price less than \$5 (to minimize potential biases arising from low-priced and illiquid stocks), using a 5-year window to estimate firms' volatility sensitivity (to mitigate the impact of outliers), and employing a one-factor model that only includes the FX volatility innovations in the first step to construct the FX volatility mimicking factor and the associated test assets. The results are all similar. To save space, we do not report these results. But they are available upon request. Therefore, all the evidence rejects the notion that the FX volatility is a priced factor in the US stock market, which calls for more research on FX risk.

Table 7 Factor-mimicking portfolio approach results based on all the currencies, 1975-2010

Panel A: Summary statistics of time-series regressions

Model	$\lvert\alpha\rvert$	$S(\alpha)$	R^2	GRS
MKT	0.31	0.20	0.66	3.59*
MKT+VOL	0.30	0.19	0.67	3.49*
MKT+SMB+HML+WML	0.23	0.13	0.83	3.58*
MKT+SMB+HML+WML+VOL	0.20	0.13	0.84	3.45*

Panel B: Two-pass OLS cross-sectional regressions

Model	Factor	γ	t_{EIV}	t_{MIS}	R^2
MKT	Alpha	1.45*	5.84	4.22	0.05
	MKT	-0.56	-1.62	-1.34	
MKT+VOL	Alpha	1.35*	5.70	3.93	0.07
	MKT	-0.46	-1.36	-1.10	
	VOL	-0.00	-1.86	-1.28	
MKT+SMB+HML+WML	Alpha	2.07*	3.96	4.00	0.81
	MKT	-1.68*	-2.68	-2.71	
	SMB	0.21	0.94	0.84	
	HML	-0.01	-0.03	-0.03	
	WML	-1.21	-1.61	-1.18	
MKT+SMB+HML+WML+VOL	Alpha	1.86*	4.06	4.02	0.89
	MKT	-1.39*	-2.52	-2.49	
	SMB	0.26	1.17	1.13	
	HML	-0.04	-0.12	-0.11	
	WML	-0.46	-0.68	-0.56	
	VOL	-0.00	-1.51	-1.49	

Table 7 summarizes time-series and OLS cross-sectional regressions when the factor-mimicking portfolio returns are used to measure FX volatility innovations and the portfolios formed on the volatility sensitivity are employed as test assets. Panel A summarizes time-series regressions to explain monthly excess returns on 25 volatility sensitivity portfolios. Panel A shows the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R2 (R2), and the GRS F-test statistic (GRS). Panel B reports the Fama and MacBeth (1973) two-pass OLS regressions with 25 volatility sensitivity portfolios as the test assets. γ is the estimated risk premium associated with each factor. tEIV and tMIS are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R2. The asterisk indicates the significance at the 5% level.

Table 8 Factor-mimicking portfolio approach results based on all the currencies: sub-sample results

Panel A: Summary statistics of time-series regressions

	1975:7 – 1985:9				1985:10 – 2010:12			
Model	|α|	S(α)	R^2	GRS	|α|	S(α)	R^2	GRS
MKT	0.54	0.30	0.72	2.99*	0.23	0.24	0.64	2.17*
MKT+VOL	0.59	0.27	0.73	2.95*	0.22	0.24	0.65	2.13*
MKT+SMB+HML+WML	0.18	0.16	0.90	2.45*	0.29	0.16	0.82	2.40*
MKT+SMB+HML+WML+VOL	0.18	0.16	0.91	2.37*	0.26	0.15	0.83	2.35*

Panel B: Two-pass OLS cross-sectional regressions

		1975:7 – 1985:9				1985:10 – 2010:12			
Model	Factor	γ	t_{EIV}	t_{MIS}	R^2	γ	t_{EIV}	t_{MIS}	R^2
MKT	Alpha	0.84	2.53	1.16	-0.04	1.43*	4.68	3.88	0.09
	MKT	0.09	0.16	0.11		-0.57	-1.38	-1.23	
MKT+VOL	Alpha	0.98	3.23	0.94	-0.08	1.35*	4.58	3.80	0.21
	MKT	-0.06	-0.11	-0.05		-0.50	-1.22	-1.10	
	VOL	0.00	0.77	0.26		0.00	-1.78	-1.49	
MKT+SMB+HML+WML	Alpha	0.47	0.83	0.79	0.89	2.05*	3.35	3.37	0.73
	MKT	-0.03	-0.04	-0.04		-1.63*	-2.17	-2.20	
	SMB	0.33	1.24	1.25		0.04	0.15	0.14	
	HML	1.66*	2.91	2.35		-0.25	-0.62	-0.55	
	WML	-0.42	-0.49	-0.43		-1.41	-1.48	-1.19	
MKT+SMB+HML+WML+VOL	Alpha	0.48	0.87	0.83	0.88	1.91*	3.46	3.45	0.81
	MKT	-0.03	-0.05	-0.05		-1.42*	-2.10	-2.09	
	SMB	0.33	1.20	1.21		0.10	0.37	0.35	
	HML	1.67*	2.83	2.31		-0.25	-0.65	-0.61	
	WML	-0.39	-0.49	-0.40		-0.76	-0.90	-0.76	
	VOL	0.00	-0.50	-0.49		0.00	-0.93	-0.92	

Panel A summarizes time-series regressions to explain monthly excess returns on 25 volatility sensitivity portfolios. Panel A shows the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R2 (R2), and the GRS F-test statistic (GRS). Panel B reports the Fama and MacBeth (1973) two-pass OLS regressions with 25 volatility sensitivity portfolios as the test assets. γ is the estimated risk premium associated with each factor. tEIV and tMIS are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R2. The asterisk indicates the significance at the 5% level.

Table 9:
Factor-mimicking portfolio approach results based on developed country currencies, 1975-2010

Panel A: Summary statistics of time-series regressions				
Model	$\lvert\alpha\rvert$	S(α)	R^2	GRS
MKT	0.30	0.20	0.66	3.08*
MKT+VOL	0.30	0.20	0.67	3.09*
MKT+SMB+HML+WML	0.23	0.13	0.83	3.01*
MKT+SMB+HML+WML+VOL	0.21	0.13	0.85	3.00*

Panel B: Two-pass OLS cross-sectional regressions					
Model	Factor	γ	t_{EIV}	t_{MIS}	R^2
MKT	Alpha	1.59*	5.95	4.28	0.09
	MKT	-0.69	-1.94	-1.56	
MKT+VOL	Alpha	1.49*	6.01	4.32	0.16
	MKT	-0.62	-1.77	-1.47	
	VOL	-0.00	-1.63	-1.43	
MKT+SMB+HML+WML	Alpha	2.17*	3.97	3.97	0.89
	MKT	-1.69*	-2.53	-2.53	
	SMB	0.29	1.42	1.39	
	HML	-0.19	-0.52	-0.51	
	WML	-0.43	-0.50	-0.46	
MKT+SMB+HML+WML+VOL	Alpha	2.02*	4.14	4.08	0.90
	MKT	-1.47*	-2.48	-2.43	
	SMB	0.32	1.56	1.53	
	HML	-0.14	-0.39	-0.39	
	WML	0.18	0.22	0.19	
	VOL	-0.00	-0.42	-0.41	

Table 9 summarizes time-series and OLS cross-sectional regressions when only the developed country currencies are used to construct the FX volatility mimicking portfolio and associated size and volatility-sensitivity portfolios. Panel A summarizes time-series regressions to explain monthly excess returns on 25 volatility sensitivity portfolios. Panel A shows the average absolute value of the intercepts (|α|), the average of the standard errors of the intercepts (s(α)), the average adjusted R2 (R2), and the GRS F-test statistic (GRS). Panel B reports the Fama and MacBeth (1973) two-pass OLS regressions with 25 volatility sensitivity portfolios as the test assets. γ is the estimated risk premium associated with each factor. tEIV and tMIS are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R2. The asterisk indicates the significance at the 5% level.

6. Conclusion

The pervasiveness of the pricing power of foreign exchange volatility across a variety of test assets (documented in Menkhoff, Sarno, Schmeling, and Schrimpf, 2011) suggests a potentially promising approach to understanding foreign exchange risk in the equity market. That is, it may be foreign exchange volatility (second moments) not foreign exchange changes (first moments) that matters for the cross-section of stock returns. This perspective also has a number of theoretical justifications. Motivated by these empirical and theoretical considerations, we explore whether foreign exchange volatility is a priced factor in the US stock market in this paper. Unfortunately, the empirical evidence in this paper suggests that foreign exchange volatility has no power to explain either the time-series or the cross-section of stock returns.

Our findings, therefore, call for more research on foreign exchange risk. In theory and practice, foreign exchange volatility can affect firms' cash flow volatility. Consequently, it should be a priced factor for equity returns. In this paper, following Menkhoff, Sarno, Schmeling, and

Schrimpf (2011), we measure foreign exchange volatility as a single variable. That is, we do not differentiate different components of volatility (i.e. long-run and short-run components). Two studies, however, suggest that it may be more informative to employ two-component volatility models. One is Bartov, Bodnar, and Kaul (1996). They find that the market risk (beta) of multinational firms increases with the increase in foreign exchange volatility when a longer-horizon (5 years) is focused upon. The second study is Adrian and Rosenberg (2008). The authors find differential effects of the long-run and short-run components of stock market volatility on expected returns of stocks. These two studies suggest that future research may decompose the foreign exchange volatility into different components and examine their differential effects on the time-series and the cross-section of stock returns.

References

Adler, M., and Dumas, B., 1983. International portfolio choice and corporate finance: a synthesis. Journal of Finance 38, 925-984.

Adrian, Tobias, and Joshua Rosenberg, 2008, Stock returns and volatility: Pricing the short-run and long-run components of market risk, Journal of Finance 63, 2997-3030.

Allayannis, G., 1997. The time-variation of the exchange rate exposure: An industry analysis, Working paper, Darden Graduate School of Business, University of Virginia

Ang, Andrew, Robert Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, Journal of Finance 61, 259-299.

Antell, J., and M. Vaihekoski, 2012, Pricing currency risk in the stock market: Evidence from Finland and Sweden 1970–2009, Journal of International Financial Markets, Institutions & Money 22, 120– 136.

Bartram, S. M., 2004. Linear and nonlinear foreign exchange rate exposures of German nonfinancial corporations, Journal of International Money and Finance 23. 673-699.

Bartram, Sohnke M., 2007, "Corporate Cash Flow and Stock Price Exposures to Foreign Exchange Rate Risk," Journal of Corporate Finance, 13, 981-994.

Bartram, Sohnke M., 2008, "What Lies Beneath: Foreign Exchange Rate Exposure, Hedging and Cash Flows," Journal of Banking and Finance, 32, 1508-1521.

Bartram, S. M., and Bodnar, G. M., 2005. The foreign exchange exposure puzzle. Working paper, John Hopkins University and Lancaster University.

Bartov, E., and G.M. Bodnar 1994. Firm Valuation, Earnings Expectations, and the Exchange Rate Exposure Effect, Journal of Finance 44:5: 1755-1785.

Bartov, Eli & Bodnar, Gordon M. & Kaul, Aditya, 1996. Exchange rate variability and the riskiness of U.S. multinational firms: Evidence from the breakdown of the Bretton Woods system, Journal of Financial Economics 42, 105-132.

Bartram, Sohnke M., G.W. Brown and B. Minton, 2010, "Resolving the Exposure Puzzle: The Many Facets of Exchange Rate Exposure," Journal of Financial Economics, 95, 148-173.

Black, F., M. C. Jensen, and M. Scholes, 1972, The Capital Asset Pricing Model: Some Empirical Findings; in Michael C. Jensen, ed.: (Praeger, New York). Studies in the Theory of Capital Markets

Bodnar, G.M., and Wong, M. H. F., 2003. Estimating exchange rate exposures: issues in model structure. Financial Management 32, 35-67.

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. Journal of Finance 52:57–82.

Chan, L. K. C., J. Karceski, and J. Lakonishok, 1998, The risk and return from factors, Journal of Financial and Quantitative Analysis 33, 159-188.

Chan, L. K. C., J. Karceski, and J. Lakonishok, 1999, On portfolio optimization: Forecasting covariances and choosing the risk model, The Review of Financial Studies 12, 937-974.

Chow, E.H., Lee, W.Y., and Solt, M.E., 1997. The exchange-rate risk exposure of asset returns. Journal of Business 70, 105-123.

Doidge, C., J. Griffin, and R. Williamson, 2006, Does Exchange Rate Exposure Matter?. Journal of Empirical Finance 13, 550-576.

Du, D., and O. Hu, 2012, Exchange rate risk in the US stock market. Journal of International Financial Markets, Institutions & Money 22, 137– 150.

Dumas, Bernard, 1978, The theory of the trading firm revisited, Journal of Finance 33. 1019-1029.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55–84.

Fama, E. F., French, K. R., 2011. Size, Value, and Momentum in International Stock Returns, Chicago Booth Research Paper No. 11-10.

Fama, E. F., and J. D. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, Journal of Political Economy 81, 607-636.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, Econometrica 57, 1121-1152.

Francis, B., I Hasan, and D. Hunter, 2008, Can hedging tell the full story? Reconciling differences in U.S. aggregate- and industry-level exchange rate risk premium, Journal of Financial Economics, 90, 169-196.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65-91.

Jorion, P., 1990. The exchange-rate exposure of U.S. multinationals. Journal of Business 63, 331-345

Jorion, P. 1991. The Pricing of Exchange Rate Risk in the Stock Market, Journal of Financial and Quantitative Analysis 26:3: 363-376.

Khoo, A., 1994. Estimation of foreign exchange rate exposure: an application to mining companies in Australia. Journal of International Money and Finance 13, 342-363.

Kolari, J., Moorman, T., and Sorescu, S. M.., 2008. Foreign Exchange Risk and the Cross-Section of Stock Returns. Journal of International Money and Finance 27, 1074-1097.

Levi, Maurice D., 1990, International finance, 2nd ed. (McGraw Hill, New York, NY).

Lewellen, J. W., Nagel, S., and Shanken, J. A., 2010. A Skeptical Appraisal of Asset Pricing Tests, Journal of Financial Economics 96, 175-194.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, Review of Economics and Statistics 47, 13-37.

Martin, A. D., and Mauer, L. J., 2005. A note on common methods used to estimate foreign exchange exposure, Journal of International Financial Markets, Institutions and Money 15, 125-140.

Menkhoff, Lukas & Sarno, Lucio & Schmeling, Maik & Schrimpf, Andreas, 2011. Carry Trades and Global Foreign Exchange Volatility, Journal of Finance, forthcoming.

Merton, R. C., 1973, An intertemporal capital asset pricing model, Econometrica 41, 867-887.

Sercu, P., 1980. A generalization of the international asset pricing model. Revue de l'Association Française de Finance 1, 91-135.

Shanken, J., 1992, On the Estimation of Beta-Pricing Models, Review of Financial Studies 5, 1-33.

Shanken, J., and G. Zhou, 2007, Estimating and Testing Beta Pricing Models: Alternative Methods and Their Performance in Simulations, Journal of Financial Economics 84, 40-86.

Shapiro, Alan C., 1974, Exchange rate changes, inflation and the value of the multinational corporation, Journal of Finance 30, 485-502.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, Journal of Finance 19, 425-442.

Solnik, B., 1974. An equilibrium model of the international capital market. Journal of Economic Theory 8, 500-524.

Vassalou, M., 2000. Exchange rate and foreign inflation risk premiums in global equity returns. Journal of International Money and Finance 19, 433-475.