Foreign Exchange Market and Equity Risk Premium Forecasting

Jun Tu[*]

Yuchen Wang

Singapore Management
University

Singapore Management
University

October 08, 2013

Foreign Exchange Market and Equity Risk Premium Forecasting

Abstract

Numerous academic studies examine equity risk premium predictability based on various macroeconomic variables and price and volume based variables from stock market. In this article, we extend the frontier of the set of predictors from macroeconomic variables and stock market variables to foreign exchange market variables due to various reasons. Firstly, foreign exchange market reflects various economic fundamentals potentially useful for predicting equity risk premium, though may not be fully reflected by available macroeconomic variables used in the literature for forecasting equity risk premium. Moreover, given that technical rules have been documented to work well in offering predicting power at foreign exchange market, price-based variables from foreign exchange market may provide useful information on predicting equity risk premium as well through the connections between foreign exchange market and stock market. We find that on top of using price and volume based variables from stock market and macroeconomic variables, incorporating price-based variables from foreign exchange market as well can not only improve the overall forecasting performance but also produce significant certainty equivalent return gain from an investment perspective.

1 Introduction

Extensive studies have examined predicting the equity risk premium based on various macroeconomic variables.[1] Ang and Bekaert (2007), Cochrane (2008), Hjalmarsson (2010), and Henkel, Martin, and Nadari (2011) find that macroeconomic variables also predict the equity risk premium across countries. Besides extensively investigating the predictive ability of macroeconomic variables (i.e.,economic fundamental), the literature has paid some attention to the value of price and volume based variables (here after: technical indicators).[2] Brock, Lakonishok, and LeBaron (1992) show that moving average generated from Dow Jones Industrial Average displays profitable trading signals. Lo, Mamaysky, and Wang (2000) present the results of automated pattern recognition analysis. Some of the recent studies further discover that the technical analysis could have equivalent or stronger predictive ability than fundamental analysis for some cases (e.g., Menkhoff and Taylor (2007) and Goh, Jiang, Tu and Zhou (2012)).[3]

However, most of the studies on predicting equity risk premium using technical analysis are limited to stock market technical indicators. To our knowledge, this article is the first to expand the frontier of technical indicators used for predicting equity risk premium from stock market to foreign exchange market. There are at least three reasons for investigating the predicting power of technical indicators from foreign exchange market on equity risk premium.[4] Firstly, given that foreign exchange market reflects economic fundamentals (e.g., Frankel and Froot (1990)), can be strongly forward-looking (e.g., Chen, Rogoff, and Rossi (2010)), and can be useful in predicting economic fundamentals (e.g., Engel and West (2005)). Therefore, it is likely that foreign exchange market can provide useful information on predicting equity risk premium of stock market that is likely driven by common economic fundamentals. Moreover, according to the Adaptive Markets Hypothesis proposed by Lo (2004), market efficiency varies across markets. For those markets that comprise of multi species of participants who are competing for scarce resources, they

---

[1]To name a few, we have Nelson (1976), Fama and Schwert (1977), Rozeff (1984), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988), Breen, Glosten and Jagannathan (1989), Lettau and Ludvigson (2001), Campbell and Vuolteenaho (2004), Guo (2006), among others.

[2]We name our price and volume based variables as technical indicators mostly to be consistent with the common way of naming them in the real world of trading by practitioners. However, it is not necessary to have to name those price and volume based variables as technical indicators. For instance, Li and Yu (2012) name their two price based indicators, which are based on the 52-week high and historical high, as two proxies for the degree of under- and over-react to news, but not as two technical indicators.

[3]There have been many surveys indicate that traders use more frequently on technical analysis than fundamental analysis, such as Schwert (1989, 1990), Billingsley and Chance (1996), Park and Irwin (2007), Covel (2009), and Lo and Hasanhodzic (2009, 2010).

[4]For theoretical models explaining the forecasting power of technical indicators, please see Treynor and Ferguson (1985), Brown and Jennings (1989) and Grundy and McNichols (1989) and Blume, Easley and O'hara(1994), among others.

tend to be more efficient than some other markets that comprise of small species of participants who are competing for abundant resources. In our study, foreign exchange market can be more efficient than stock market in terms of incorporating relevant information for forecasting equity risk premium. This is because that a large number of participants, such as central banks, currency speculators, organizations, governments, retail investors and international investors, are chasing only those few major currencies in foreign exchange market while stock market investors have to select among thousands of different stocks in stock market. Therefore, the technical indicators that generated from the relatively more efficient foreign exchange market may reveal additional information useful for predicting the equity risk premium but not yet incorporated by the relatively less efficient stock market.

Secondly, there are some studies that report the evidence of the connection between foreign exchange market and stock market (e.g., Jorion (1991), Choi, Hiraki and Takezawa (1998), and Hau and Rey (2006)). In addition, it is documented that technical rules work well in offering predicting power at foreign exchange market. Osler (2003) provides some explanations on the success of technical analysis for predicting exchange rates. Moreover, Neely, Weller and Dittmar (1997), LeBaron (1999), Neely (2002), among others, find the profitability of technical indicators in foreign exchange market. Hence, the technical indicators from foreign exchange market may provide useful information on predicting equity risk premium of stock market through the connections of the two markets.[5]

Thirdly, we find that the technical indicators from foreign exchange market predict investors' changes of sentiment as well and better than the technical indicators from stock market. In addition, the changes of sentiment are correlated with stock returns. This provides another reason for using technical indicators from foreign exchange market in predicting equity risk premium of stock market.

In this article, we investigate 1): whether technical indicators from foreign exchange market have any ability to predict equity risk premium; And more importantly, 2): whether technical indicators from foreign exchange market can provide additional information beyond economic variables and technical indicators from stock market for predicting equity risk premium. Given that the forecasting power of a predictor may change across different periods or market conditions, we generate all forecasts using a two-regime predictive regression framework, where the regime is determined by the sentiment changes index of Baker and Wurgler (2007). And to extract main information from massive number of predictors, we use principal component analysis.

---

[5]The profitability of technical indicators in foreign exchange market does not necessarily imply that foreign exchange market is inefficient or more inefficient than stock market. For instance, Kho (1996) shows time varying risk premium and volatility can explain the profitability of technical trading rules.

In our empirical analysis, we employ both in-sample and out-of-sample tests, given that both approaches have their own relative strength. In-sample estimation shows more power in detecting the existence of return predictability, more efficient parameter estimates and more precise estimates of equity risk premium. While out-of-sample estimation implies the stability of the data-generating process, prevents the in-sample over-fitting problem and is more relevant for investors. Hence, by using both methods, we ensure the robustness of our results. Our data are from 1971:01 to 2010:12 including the 14 macroeconomic variables in Goyal and Welch (2008), 56 technical indicators from stock market and 35 technical indicators from foreign exchange market based on popular technical rules, such as moving average, on-balance volume, relative strength index and momentum.

In-sample results demonstrate that individual technical indicators typically perform as well as individual macroeconomic variables for predicting the future equity risk premium. In sample predictive regression based on principal components extracted from the 35 technical indicators of foreign exchange market (FX) performs about the same as the predictive regression based on principal components generated from the 56 technical indicators of stock market (SM) with an R^2 of 1.82% for FX and an R^2 of 1.81% for SM. And for the predictive regression based on principal components generated from the 14 macroeconomic variables (ECON), it performs with the largest R^2 of 1.96% among these three individual cases. Moreover, by integrating FX into the combination of SM and ECON, which represented by FX+SM+ECON, the in-sample R^2 increased from 2.54% to 2.98%, an about 17% gain, indicating that FX indeed captures additional information that is relevant for predicting the equity risk premium beyond the combination of ECON and SM. Out-of-sample results show FX contains additional information as well. For instance, FX displays better out-of-sample predictive performance than SM with a larger R^2_{os} of 3.52% than an R^2_{os} of 1.79% for SM. Moreover, the incorporation of FX with SM (denoted as FX+SM) also performs better than using SM alone out-of-sample with a larger R^2_{os} of 3.29% for FX+SM than an R^2_{os} of 1.79% for SM. These results show that FX likely contains useful information for predicting equity risk premium and the information captured by FX are not redundant to the information captured by SM. Furthermore, the incorporation of FX on top of SM and ECON into the predictive regression increases the out-of-sample R^2_{os} from 2.02% to 3.40%, a more than 68% increase! Therefore equity risk premium forecasts can be improved by utilizing FX on top of technical indicators from stock market and macroeconomic variables. In line with this finding, we also find that incorporating information from technical indicators from foreign exchange market on top of technical indicators from stock market and macroeconomic variables offers substantial certainty equivalent return gain to investors by better tracking the substantial fluctuations in the equity risk premium.

The rest of the paper is organised as follows. Section 2 introduces the econometric method-

ology. Section 3 displays the empirical regression and the economic significance indicated by certainty equivalent return gain. Section 4 concludes.

2 Econometric methodology

This section introduces the econometric framework, which includes the description of our regression model, the construction of predictors and the evaluation method of forecasting performance.

2.1 Regression model

The conventional standard predictive regression model for forecasting the in-sample equity risk premium is

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \tag{1}$$

where r_{t+1} is the excess return of broad stock market index, x_t is the predictor available at t, and ε_{t+1} is the zero-mean disturbance term. Then the out-of-sample prediction of the next period's equity risk premium based on equation (1) should be given by

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t \tag{2}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{r_i\}_{i=2}^{t}$ on a constant and $\{x_i\}_{i=1}^{t-1}$. In this paper, we extend the standard predictive regression model indicated by equation (1) to two-regime predictive regression in order to allow for asymmetric reactions of the stock market to its predictors.[6] The up-regime and down-regime are determined by the changes of sentiment as follows,

$$I_t = \begin{cases} 1, & \text{if } \Delta SENT_t \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

---

[6]Due to the asymmetries of stock returns in up- and down- markets, the two-regime predictive regression method is also used by Lettau and Nieuwerburgh (2008), Henkel, Martin, and Nardari (2011) and Pettenuzzo and Timmemann (2011) though none of them use the sentiment changes index to determine regimes. In addition, Ang and Chen(2002) and Cooper, Gutierrez, and Hameed (2004) have characterized the stock price movements as up- and down- markets.

The sentiment changes index $\Delta SENT$ followed by Baker and Wurgler (2007)[7] is the first principal component of changes in six measures of sentiment: the closed-end fund discount (CEFD), de-trended log turnover (TURN), the number of IPOs (NIPO), the first-day return on IPOs (RIPO), the dividend premium (PDND), and the equity share in new issues (S), each standardized and with the effect of macroeconomic conditions removed. $\Delta SENT$ is standardized to have zero mean and unit variance over the full sample period.

$$\Delta SENT = -0.17\Delta CEFD + 0.32\Delta TURN + 0.17\Delta NIPO + 0.41\Delta RIPO - 0.49\Delta PDND - 0.28\Delta S$$
(4)

If the indicator I_t is 1 then it is defined as an up-regime which has an increase of sentiment. Otherwise, it is a down-regime which has a decrease of sentiment.

In order to capture the regime dependent forecasting power of predictors in the two regimes, we extend the one-regime predictive regression model into

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta^{up}x_t + \varepsilon_{t+1}^{up}, & I_t = 1 \quad up-regime \\ \alpha^{down} + \beta^{down}x_t + \varepsilon_{t+1}^{down}, & I_t = 0 \quad down-regime \end{cases}$$
(5)

We estimate this two-regime regression using monthly data from Goyal and Welch (2008). The equity risk premium is the difference between the log return on the S&P 500 index(including dividends) and the log return on a risk-free bill. For the predictors in this paper, we separate them into three classifications: 14 macroeconomic variables, 56 technical indicators from stock market and 35 technical indicators from foreign exchange market based on four popular technical strategies.

2.2 Macroeconomic variables

The following 14 macroeconomic variables are representative of Goyal and Welch (2008) and comprise the set of x_t variables used to estimate the equity risk premium in equation (5):

1. *Dividend-price ratio* (DP): log of a twelve-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).

2. *Dividend yield* (DY): log of a twelve-month moving sum of dividends minus the log of lagged stock prices.

---

[7]Since Baker and Wurgler (2007) suggest that sentiment changes index, not sentiment level index, has a highly significant correlation with speculative demand which makes it be able to largely capture the prevailing "greed" versus "fear" or "bullish" versus "bearish" notion, we use the sentiment changes index instead of sentiment level index to determine the two regimes.

3. *Earnings-price ratio* (EP): log of a twelve-month moving sum of earnings on the S&P 500 index minus the log of stock prices.

4. *Dividend-payout ratio* (DE): log of a twelve-month moving sum of dividends minus the log of a twelve-month moving sum of earnings.

5. *Stock variance* (SVAR): monthly sum of squared daily returns on the S&P 500 index.

6. *Book-to-market ratio* (BM): book-to-market value ratio for the Dow Jones Industrial Average.

7. *Net equity expansion* (NTIS): ratio of a twelve-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.

8. *Treasury bill rate* (TBL): three-month Treasury bill interest rate (secondary market).

9. *Long-term yield* (LTY): long-term government bond yield.

10. *Long-term return* (LTR): return on long-term government bonds.

11. *Term spread* (TMS): long-term yield minus the Treasury bill rate.

12. *Default yield spread* (DFY): difference between Moody's BAA- and AAA-rated corporate bond yields.

13. *Default return spread* (DFR): long-term corporate bond return minus the long-term government bond return.

14. *Inflation* (INFL): calculated from the Consumer Price Index (CPI) for all urban consumers; We use the x_{t-1} in our regression for inflation to account for the delay in CPI releases.

2.3   Technical indicators from stock market and foreign exchange market

The reason why we predict the equity risk premium using technical indicators based on foreign exchange market instead of lagged foreign exchange market returns is that prices move up and down around the primary (or long-run) trend that may not be well captured by a single lagged return, while technical indicators can be constructed with data over multiple time frames, from one month to multi year horizons so that investors can build a better forecasting through discovering

patterns over these multiple time frames.[8] The technical indicator rules we applied here can be divided into two types: trend-following indicators and oscillators. For the trend following indicators, which include moving average, on-balance volume and others, are coincident or lagging indicators. They turn after trends reverse. And for the oscillators, we use the relative strength index and momentum which help identify turning points. These oscillators are leading indicators which often turn ahead of prices. The first technical strategy is moving average (MA), which produces a buy or sell signal ($S_t=1$ or $S_t=0$, respectively) at the end of period t by comparing two kinds of moving average:

$$S_t = \begin{cases} 1 & if \quad MA_{s,t} \geq MA_{l,t} \\ 0 & if \quad MA_{s,t} < MA_{l,t} \end{cases} \tag{6}$$

where

$$MA_{j,t} = (1/j)\sum_{i=0}^{j-1} P_{t-i} \quad for \quad j=s,l; \tag{7}$$

P_t is the level of a stock price index (for stock market) or a GBP/USD exchange rate (for foreign exchange market), $s(l)$ is the length of the short (long) MA ($s < l$). We denote the MA indicator with MA lengths s and l as $MA_{s,l}$. Intuitively, the MA rule detects changes in stock price or foreign exchange rate trends, because MA_s will be more sensitive to recent price change than the MA_l. For instance, if the prices have been recently downward, the MA_s will become lower than the MA_l. But when the prices begin to trend upward, the MA_s will increase faster than the MA_l, eventually overtaking the MA_l and indicating a buy signal ($S = 1$). We analyze monthly rules with $s=1$, 2, 3 and $l=6$, 9, 12, 15, 18, 21, 24 in order to cover a wide range of combinations of s and l. Therefore there will be 21 MA indicators for both stock market and foreign exchange market.

The second technical strategy is on-balance volume (OBV), which is frequently employed by technical analysts to identify market trends. The OBV is defined as follows:

$$OBV_t = \sum_{k=1}^{t} VOL_k D_k \tag{8}$$

where VOL_k is the measurement of the trading volume during period k, while D_k is the binary variable that takes a value of 1 if $P_k - P_{k-1} \geq 0$ and -1 otherwise. To coordinate with MA, we form a trading signal from OBV_t as

$$S_t = \begin{cases} 1 & if \quad MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0 & if \quad MA_{s,t}^{OBV} < MA_{l,t}^{OBV} \end{cases} \tag{9}$$

---

[8]For stock market, Neely, Rapach, Tu and Zhou (2012) explain the reasons of using technical indicators instead of lagged stock returns to predict equity risk premium.

where

$$MA_{j,t}^{OBV} = (1/j) \sum_{i=0}^{j-1} OBV_{t-i} \quad for \quad j = s, l \tag{10}$$

Intuitively, a buy signal will be generated by a strong positive market trend which indicates relatively high recent volume and recent price increase. To be consistent with the choice of s and l for the MA rule, we compute the monthly OBV signal for s=1, 2, 3 and l=6, 9, 12, 15, 18, 21, 24 and denote the corresponding indicator as $OBV_{s,l}$, which will produce 21 OBV indicators that cover a wide range of combinations of s and l. In addition, since foreign exchange market is decentralized, there are no comprehensive indicators of volume which make foreign exchange volume data remains difficult to track. Therefore, due to the unavailability of the volume data in foreign exchange market to us, we only use on-balance volume indicators for stock market.

The third technical strategy that we considered is the Relative Strength Index (RSI), which can be computed by Relative Strength (RS):

$$RS_{m,t} = \frac{average\ of\ net\ UP\ changes\ for\ m\ months}{average\ of\ net\ DOWN\ changes\ for\ m\ months}$$

$$\tag{11}$$

$$RSI = 100 - \frac{100}{1+RS}$$

UP corresponds to the case that the S&P 500 index or foreign exchange rate is higher than the month before. Down corresponds to the case that the S&P 500 index or foreign exchange rate is lower than the month before. Hence the average of net UP changes for m months can be obtained through adding up the amount of increases for all UP within m months and dividing this sum by m. The same approach applies for average of net DOWN changes for m months. We produce the monthly RSI_m indicators for $m = 6, 9, 12, 15, 18, 21, 24$, which generated seven RSI indicators that cover a wide range of combinations of s and l for both stock market and foreign exchange market.

The fourth technical strategy is based on momentum (MOM), which belongs to the second type of indicators – oscillators. We get the signal from the momentum rule, MOM_m, as follows:

$$S_t = \begin{cases} 1 & if \quad P_t \geq P_{t-m} \\ 0 & if \quad P_t < P_{t-m} \end{cases} \tag{12}$$

Intuitively, a positive MOM_m means current stock price or foreign exchange rate is higher than its level at m periods ago and this will result in relatively high expected excess return, such that we get a buy signal. We assign 6, 9, 12, 15, 18, 21 and 24 to m, which will produce seven MOM indicators that cover a wide range of combinations of s and l for both stock market and foreign exchange market.

Overall we have 35 technical indicators generated from foreign exchange market using MA, RSI and MOM technical rules and 56 technical indicators generated from stock market using MA, OBV, RSI and MOM technical rules. Since 91 technical indicators in total are enormous, we implement Principal Component Analysis (PCA) method on those technical indicators for extracting information from each market. The principal component analysis integrates information from a large number of potential predictors in predictive regressions. The first few principal components identify the key co-movements among the entire set of predictors, which filter out much of the noise in individual predictors, thereby avoid the over-fitting problem.

2.4 Predictive analysis with both macroeconomic variables and technical indicators

To compare and combine the predictability of the three channels, namely, macroeconomic variables, stock market technical indicators and foreign exchange market technical indicators, we examine the performance of seven cases as follows:

1. ECON: the first principal component of 14 macroeconomic variables in Table 2 as predictor,

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} ECON_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} ECON_t + \varepsilon_{t+1}^{down} \end{cases} \tag{13}$$

2. SM: the first principal component of the 56 technical indicators for stock market as predictor,[9]

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} SM_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} SM_t + \varepsilon_{t+1}^{down} \end{cases} \tag{14}$$

3. FX: the first principal component of the 35 technical indicators for foreign exchange market as predictor,

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} FX_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} FX_t + \varepsilon_{t+1}^{down} \end{cases} \tag{15}$$

4. SM+ECON: the principal components of SM and ECON in equations (14) and (13) as predictors,

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} SM_t + \beta_2^{up} ECON_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} SM_t + \beta_2^{down} ECON_t + \varepsilon_{t+1}^{down} \end{cases} \tag{16}$$

---

[9]The regression coefficients α and β and residual ε_{t+1} are different across the seven cases here.

5. FX+ECON: the principal components of FX and ECON in equations (15) and (13) as predictors,

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up}FX_t + \beta_2^{up}ECON_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down}FX_t + \beta_2^{down}ECON_t + \varepsilon_{t+1}^{down} \end{cases} \quad (17)$$

6. FX+SM: the first and second principal components generated from all the 91 technical indicators as predictors,[10]

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up}PC_t^1 + \beta_2^{up}PC_t^2 + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down}PC_t^1 + \beta_2^{down}PC_t^2 + \varepsilon_{t+1}^{down} \end{cases} \quad (18)$$

7. FX+SM+ECON: the first and second principal components generated from the 91 technical indicators, and together with the principal component ECON in equation (13) as predictors.

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up}PC_t^1 + \beta_2^{up}PC_t^2 + \beta_3^{up}ECON_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down}PC_t^1 + \beta_2^{down}PC_t^2 + \beta_3^{down}ECON_t + \varepsilon_{t+1}^{down} \end{cases} \quad (19)$$

By comparing the performance of the above seven cases, we are able to examine the predictability of equity risk premium based on each one of the three channels, namely, technical indicators from foreign exchange market, technical indicators from stock market and macroeconomic variables, and the predictability of combining any two or all three of them. Recently, Neely, Rapach, Tu and Zhou (2012), among others, have investigated the predictability of equity premium based on technical indicators from stock market together with macroeconomic variables. However, to our knowledge, there is no study so far that has studied the predictability of equity risk premium based on three channels, technical indicators from foreign exchange market on top of technical indicators from stock market and macroeconomic variables. In our study, by comparing the case 7 and the case 4, namely, equation (19) and equation (16), we are able to tell how much additional predicting power can be obtained by incorporating technical indicators from foreign exchange market on top of technical indicators from stock market and macroeconomic variables.

---

[10]Given FX and SM are both based on technical strategies, we combine them together and take the first two principal components in order to distinguish FX+SM from the fundamental predictor which is the first principal component of 14 macroeconomic variable indicated by ECON. But we also use FX from equation (15) and SM from equation (14) as two predictors for this regression model. The result is similar to using FX+SM in case 6 here.

2.5 Measurement of performance

In order to analyze the forecasting performance among different kinds of predictors, according to Campbell and Thompson (2008), we use out-of-sample R_{os}^2 to measure the out-of-sample performance, which can be calculated from

$$R_{os}^2 = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2} \tag{20}$$

where T is the out-of-sample evaluation period data amount, $\hat{r}_t$ is the excess return forecast estimated from regression (4) by using the data up to month $t-1$, and $\bar{r}_t$ is the historical average return generated from the data up to month $t-1$. The R_{os}^2 statistics measure the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast relative to the historical average. A positive R_{os}^2 means a lower MSFE for the forecast based on the predictor relative to the forecast based on the historical average return which implies a feasible predictor. All the forecasts are calculated using recursive method. We use the first 240 months as training period and the remaining 216 months as out-of-sample evaluation period indicated by T, which is from Jan, 1993 to Dec, 2010. We also implement a test based on the p-value of the Clark and West (2007) MSFE-adjusted statistic. It tests the null hypothesis that the $R_{os}^2 \leq 0$ which means the MSFE of that forecast is greater than or equal to the MSFE of historical average return. And the alternative hypothesis is $R_{os}^2 > 0$ implies that predictor outperform historical average.

3 Empirical results

This section introduces the data sets and reports both in-sample and out-of-sample results. These results are based on each one of the three channels, namely, technical indicators from foreign exchange market, technical indicators from stock market and macroeconomic variables, and combinations of any two or all three of them. In addition, in this section, we analyze the reasons behind the predictability of technical indicators from foreign exchange market and report the certainty equivalent return gain of utilizing technical indicators from foreign exchange market to predict equity risk premium for a mean-variance investor.

3.1 Data

In addition to the monthly data from Goyal and Welch (2008), we also use the exchange rate data of GBP/USD. We choose GBP/USD for a few reasons. According to the average daily volume

composition which is reported by the foreign exchange committee, GBP/USD is nearly always the third largest among all currency pairs, just after EUR/USD and JPY/USD. However, JPY is one of the favoured currencies as the borrowing part of carry trade because of the near-zero interest rate in Japan for recent years that makes it less connected to fundamentals. And EUR/USD has much shorter data period than GBP/USD. Given the GBP/USD rate we obtain from the website of FRED is available from 1971:01, and the first 24 months data are used for calculating the first set of technical indicators, our in-sample period starts from 1973:01 and ends in 2010:12. As for the out-of-sample period, it is from 1993:01 to 2010:12 given that we use the first 240 months from 1973:01 to 1992:12 as the initial estimation period. Table 1 reports the summary statistics for the equity risk premium and 14 macroeconomic variables for 1973:01-2010:12. The start of the sample reflects data availability for the technical indicators. The end of the sample indicates data availability for the sentiment changes index which was mentioned to be used for the separation of two regimes. The average monthly equity risk premium is 0.32%, divided by its monthly standard deviation of 4.59%, produces a monthly Sharpe ratio of 0.07.

3.2 Predictive performance based on individual predictors

Table 2 reports the result of using each one of 14 macroeconomic variables to predict the equity risk premium based on the two-regime predictive regression model. The first column reports the variable x_t used for prediction in the equation (5). The second and third columns report the slope coefficients in up-regime (β^{up}) and down-regime (β^{down}). In addition, all the t-statistics are shown in the brackets beside them. The fourth and fifth columns report the in sample R^2 in the up-regime (R^2-up) and down-regime (R^2-down). While the seventh and eighth columns report the R^2_{os} in the up-regime (R^2_{os}-up) and down-regime (R^2_{os}-down). To measure the performance of each individual predictor, the overall R^2 and R^2_{os} are reported in the sixth and ninth columns, respectively.

As shown in the second column of Table 2, out of 14 macroeconomic variables, five are significant in up-regime, which are earning-price ratio (EP), stock variance (SVAR), treasury bill rate (TBL), term spread (TMS) and default return spread (DFR). As shown in the third column of Table 2, four exhibit significant predictive ability in down-regime, which are dividend-price ratio (DP), dividend yield (DY), earning-price ratio (EP) and stock variance (SVAR). Hence, there are only two predictors, EP and SVAR, have significant predictability in both up- and down- regimes. In the sixth column, all the predictors have positive in-sample R^2, ranging from 1.22% (NTIS) to 3.62% (DFR), which are much better than the result without using two-regime approach. For instance, the result of regression (1) (not reported in Table 2) shows that only five predictors have positive in-sample R^2, which are DY, SVAR, LTR, TMS and DFR. However, all these five posi-

tive R^2 are smaller than the corresponding R^2 using equation (5). Out-of-sample results also show a better predictability by using two-regime approach. Therefore, consistent with literature, it is likely that the predictive ability of macroeconomic variables varies across time and across different market conditions. In the ninth column, three out of 14 exhibit 1% significant out-of-sample predictive ability (DP, DY, BM), three shows 5% significance (EP, LTY, DFR) and TBL indicates 10% significance.[11] Therefore, after using sentiment changes index to separate market into up- and down- regimes, seven macroeconomic variables exhibit better forecasting performance than historical average in predicting the equity risk premium.[12]

And for technical indicators, which are not reported in the table since the enormous amount, all of the 91 technical indicators have positive in-sample R^2 after using two-regime approach and there are 78 out of 91 technical indicators that have at least 10% significance for out-of-sample R^2_{os}. Among them, 47 have 1% significance, which are 27 out of 35 technical indicators from foreign exchange market and 21 out of 56 technical indicators from stock market. In addition, almost all of the foreign exchange market technical indicators, 34 out of 35 show better performance versus historical average return, while 44 out of 56 stock market technical indicators display better performance relative to historical average in forecasting equity risk premium.

Overall, there are some predictors in each one of the three channels that can predict equity risk premium. Within each channel, some predictors perform better than others. In addition, the two-regime predictive regression model tends to perform better than the conventional single regime predictive regression. Therefore, we use the two-regime model in our study for forecasting equity risk premium.

3.3   Predictive performance based on combined information

Now we further examine predictive performance based on combined information over the three channels, namely, technical indicators from foreign exchange market (FX), technical indicators from stock market (SM) and macroeconomic variables (ECON). Table 3 reports the results. The first column lists out the seven kinds of combination we consider. The second and third columns report the slope coefficients in up-regime (β^{up}) and down-regime (β^{down}). In addition, all the t-statistics are shown in the brackets beside them. The fourth and fifth columns report the in sample R^2 in the up-regime (R^2-up) and down-regime (R^2-down). While the seventh and eighth

---

[11]In contrast to the lack of out-of-sample predicting power of the 14 macroeconomic variables documented in Goyal and Welch (2008), when using two-regime predictive regression based on sentiment changes index, many macroeconomic variables show strong predictability.

[12]As shown in the second and third columns of Table 2, most of the 14 macroeconomic variables perform differently across up- and down- regimes

columns report the R_{os}^2 in the up-regime (R_{os}^2-up) and down-regime (R_{os}^2-down). To measure the performance of each individual predictor, the overall R^2 and R_{os}^2 are reported in the sixth and ninth columns, respectively.

First of all, we illustrate how the 35 technical indicators from foreign exchange market are aggregated to form the combined indicator labelled as FX in Table 3. The combined FX indicator is the first principal component of the 35 technical indicators from foreign exchange market with the principal component weights documented by the first two pictures of Figure 1 for the up- and down- regimes. Interestingly, as shown by the first and the second pictures in figure 1, the weights are similar across the five groups: $MA_{1,6}$ to $MA_{1,24}$, $MA_{2,6}$ to $MA_{2,24}$, $MA_{3,6}$ to $MA_{3,24}$, RSI_6 to RSI_{24} and MOM_6 to MOM_{24} for both up- and down- regimes. Therefore, this 'almost-equal-weight' pattern indicates that the combined FX indicator acts like a consensus indicator that averages out the information across the five groups of indicators with almost an equal weight. And this 'almost-equal-weight' pattern also more or less holds for the SM case as shown in the third and fourth pictures of Figure 1. As a result, the combined SM indicator can also be interpreted as some sort of consensus indicator across eight groups for the stock market, which are $MA_{1,6}$ to $MA_{1,24}$, $MA_{2,6}$ to $MA_{2,24}$, $MA_{3,6}$ to $MA_{3,24}$, $OBV_{1,6}$ to $OBV_{1,24}$, $OBV_{2,6}$ to $OBV_{2,24}$, $OBV_{3,6}$ to $OBV_{3,24}$, RSI_6 to RSI_{24} and MOM_6 to MOM_{24}. As for the case of ECON, the 14 macroeconomic variables are aggregated to form the combined ECON indicator, which is the first principal component of 14 macroeconomic variables. The weights of the 14 macroeconomic variables are not reported in figure 1 to save space. In addition, the weights of the 14 macroeconomic variables are not almost equal. Hence, not like the cases of FX and SM, the combined ECON indicator does not act as a consensus indicator across various 14 macroeconomic variables. This difference between the combined ECON indicator and the combined FX or SM indicator implies that the channel of ECON and the channels of FX and SM reflect information at different manners. In addition, we find out that the three channels may capture different information relevant for predicting equity risk premium as shown later in this article.[13]

When the combined FX indicator or the combined SM indicator used as the predictor, corresponding to regression (15) or (14), as shown in Table 3, FX has a much better out-of-sample performance with an R_{os}^2 of 3.52%, an R_{os}^2-up of 4.60% and an R_{os}^2-down of 2.57% compared to an R_{os}^2 of 1.79%, an R_{os}^2-up of 3.35% and an R_{os}^2-down of 0.42% for SM. Even though in-sample results show that FX and SM perform almost the same in predicting equity risk premium, combining the in-sample and out-of-sample results indicates that the foreign exchange market is at least equally important as stock market in terms of providing relevant technical indicators for forecast-

---

[13] Again, same as in the case of macroeconomic variables, as shown in the second and third columns of Table 3, FX and SM perform differently across up- and down- regimes.

ing equity risk premium. When the combined ECON indicator (the first principal component of 14 macroeconomic variables) is used as the predictor in regression (13), the out-of-sample R^2_{os} is 2.02% at significance level 1% and shows better forecasting ability in the up-regime than in the down-regime, since R^2_{os}-up has a larger value of 2.73% than a value of 1.4% for R^2_{os}-down. Both R^2_{os}-up and R^2_{os}-down are significant at significance level 5%. Across the three channels, ECON has the best in-sample R^2 statistics, while FX has the best out-of-sample R^2 statistics.

In addition, when predicting the equity risk premium, the existing literature normally either uses macroeconomic variables alone or combines them with technical indicators from stock market. Hence we also report the result of using regression (16), as shown in the row SM+ECON. The result shows that combining SM with ECON can improve the in-sample performance from using either SM or ECON alone though the improvement for the out-of-sample performance is mixed. It does improve the out-of-sample result of using SM alone, though does not improve the result of using ECON alone. More interestingly, the performance of combining SM with ECON is even worse than using FX alone in terms of out-of-sample performance, though for the in-sample performance, SM+ECON is still somewhat better. However, when FX is combined with ECON indicated by equation (17), then it dominates SM, ECON and the combination predictive approach, SM+ECON, for out-of-sample overall period, for the up-regime and for the down-regime. For instance, FX+ECON has a larger R^2_{os} of 3.54% than 1.79% (SM), 2.02% (ECON) and 2.02% (SM+ECON). Moreover, the FX+SM of regression (18) performs better than using SM alone for both in-sample and out-of-sample cases with a larger in-sample R^2 of 2.00% for FX+SM than an R^2 of 1.81% for SM and a larger R^2_{os} of 3.29% for FX+SM than an R^2_{os} of 1.79% for SM.

Furthermore, as shown in the last row, when FX+SM is further combined with ECON, which indicates by regression (19), it dominates all the three individual cases, ECON, SM and FX, and the three bivariate combination cases, SM+ECON, FX+ECON and FX+SM for both in-sample and out-of-sample. Therefore, combining the information from all three channels preforms the best. Particularly, the incorporation of FX on top of SM and ECON into the predictive regression increases the in-sample R^2 by about 17% from 2.54% to 2.98% and increases the out-of-sample R^2_{os} from 2.02% to 3.40% by more than 68%![14] Moreover, without adding FX into the predictive regression, SM+ECON has smallest forecasting power among all predictors during the down-regime

---

[14]Since the macroeconomic variable, DFR, has the largest in-sample and out-of-sample R-squared, we also examine the case that replace ECON with DFR for equation (13), (17), (16) and (19). The results show better predictability of ECON, FX+ECON, SM+ECON and FX+SM+ECON for both in-sample and out-of-sample. And by adding FX into ECON, R^2 increased from 3.56% to 4.06%, while R^2_{os} increased from 4.80% to 6.72% which is 40% increase. The predictability also improved by adding FX into SM+ECON which generates a higher R^2 of 4.42% and R^2_{os} of 6.47%. Therefore, even some investors can use DFR to forecast by identifying it as the best economic variables for forecasting equity premium beforehand without looking at the whole sample data, FX can still provide additional information beyond ECON and even SM+ECON.

as evidenced by the insignificant R^2_{os}-down of 0.28%. In contrast, with the incorporation of FX into the predictive regression, FX+SM+ECON has significant and larger R^2_{os}-down of 0.86%.[15] Therefore, comparing with the combination of ECON and SM, incorporating technical indicators from foreign exchange market (FX) on top of technical indicators from stock market (SM) and macroeconomic variables (ECON) can not only improve the overall predicting performance but also increase the stability of the forecasting performance across different market conditions like up- and down- regimes based on the sentiment changes index.

Given that the up- and down- regimes are determined based on the Baker and Wurgler sentiment changes index that is not a real time sentiment changes index[16], our out-of-sample results may contain some look-ahead bias. However, the influence of this potential look-ahead bias should be relatively small and does not affect our results that much based on the following reasons.

Firstly, Baker and Wurgler's sentiment changes index only has a R^2_{os} of 0.1% in predicting equity risk premium, which indicates that the sentiment changes index does not help much in predicting equity risk premium even its weights are estimated using the whole sample. Therefore even the up- and down- regimes separation process may contain some look-ahead bias, the results are not likely to be affected much by this bias. Secondly, we replace the Baker and Wurgler's sentiment changes index with an alternative sentiment changes index: the University of Michigan Consumer Sentiment Changes Index.[17] This index is a survey based on measure, which means that the changes of sentiment are collected for every month without using the future information. By using this index to separate up- and down- regimes for predicting the equity risk premium, FX has the highest R^2_{os} of 2.61% among three individual cases, ECON, SM and FX. And after incorporating FX with ECON, the R^2_{os} increased from 1.89% (ECON) to 3.56% (FX+ECON). Therefore, after using alternative index without look-ahead bias, the result still holds. For instance FX can still provide additional information for predicting equity risk premium. In order to further confirm that the look-ahead bias does not have much influence, thirdly, we run out-of-sample analysis based on a real time sentiment changes index. The real time sentiment changes index is derived from the same component proxies of the Baker and Wurgler's sentiment changes index though the weights in equation (4) are estimated through a recursive process using only the information up to the current month t. We then use this index, which does not contain any look-ahead bias, to separate the

---

[15]We also examine the performance across recessions and expansions over business cycles. The unreported results are more or less similar to those reported here corresponding to the case of splitting sample into up- and down- regimes according to the sentiment changes index.

[16]The weights of the six components of the Baker and Wurgler sentiment changes index are generated based on the whole sample.

[17]This index has also been used by Ludvigson (2004), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), and Shen and Yu (2012). The data period is from 1978:01 to 2010:12. We use the first 180 months as the initial period and the rest 215 months as the evaluation period for the out-of-sample analysis.

up- and down- regimes for predicting the equity risk premium. The results still indicate that FX can provide additional information beyond ECON and SM for predicting equity risk premium.[18] Since the look-ahead bias does not have much influence, in order to be consistent with the literature, we use Baker and Wurgler's sentiment changes index in this study.

The next section provides some potential reasons for why FX can offer additional predicting power in forecasting equity risk premium beyond ECON and SM.

3.4 Reasons for the additional predictability of foreign exchange market

In order to understand why FX can offer additional predicting power in forecasting equity risk premium beyond ECON and SM, we show that FX does contain useful information for predicting equity risk premium beyond the information captured by SM and ECON. Firstly, for the case of FX+SM, which are the first two principal components of the 91 technical indicators including the 35 technical indicators from foreign exchange market and the 56 technical indicators from stock market, we report the weights of the first and second principal components of the 91 technical indicators in the Figure 2. By comparing the four pictures in Figure 1 with the four pictures in Figure 2, it appears that FX tends to perform a relatively dominant role in the second principal component for both up- and down- regimes while SM tends to perform a relatively leading role in the first principal component. This clearly demonstrates that FX captures different information from those captured by SM. Hence, not surprisingly, we find that incorporating FX on top of SM as in the case of FX+SM can improve the predictability from using SM alone.

Secondly, given that FX can strongly predict equity risk premium, it is interesting to see whether SM can also strongly predict foreign exchange market returns. We provide a simple check on this and the results are reported in Panel B of Table 4. For comparison purpose, we also report the results about using FX to predict equity risk premium of stock market in Panel A of Table 4. We use two types of predictive regression models.

The first one is based on the standard one-regime predictive regression model.

$$r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{21}$$

---

[18]The R^2_{os} of those predictors are relatively smaller than the R^2_{os} in Table 3. The relatively smaller R^2_{os} can be due to the relatively larger estimation errors. The real time sentiment changes index we generated needs to estimate the weights for each month. And the aggregation of estimation errors across over 200 months can create substantial amount of estimation errors. In contrast, Baker and Wurgler's sentiment changes index is subject to relatively small estimation errors since it is created by using the whole sample to estimate the principal component weights. Finding a good real time sentiment index without suffering too much of the estimation errors could be an interesting topic for future research.

The second one is based on the two-regime predictive regression model separated by the sentiment changes index as in Table 3.

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} X_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} X_t + \varepsilon_{t+1}^{down} \end{cases} \tag{22}$$

As shown in Panel A of Table 4, the R^2 of FX for predicting equity risk premium of stock market is relatively high for both one- and two- regime predictive regressions. In contrast, the R^2 statistics of SM for predicting foreign exchange market returns as shown in Panel B are relatively much lower, 0.07 for the one-regime predictive regression and 0.64 for the two-regime predictive regression. Therefore, equity risk premium of stock market can be predicted by some public information, such as FX. In contrast, foreign exchange market returns cannot be predicted by SM. This indicates that FX contains useful information for predicting equity risk premium of stock market while SM does not contain much useful information for predicting foreign exchange market returns. The larger magnitude of the regression coefficient β and the t-statistic for the case of using FX to predict equity risk premium of stock market than for the case of using SM to predict foreign exchange market returns also indicates that FX contains useful information for predicting equity risk premium of stock market while SM does not contain much useful information for predicting foreign exchange market returns.

In the sense that foreign exchange market returns cannot be predicted by some public available information, like SM, while equity risk premium of stock market can be predicted by some public available information, like FX, this result is to some extend related to the adaptive market hypothesis of Lo (2004). Foreign exchange market, as one of the largest financial markets in the world, has a very large number of diverse market participants, such as central banks, global funds, retail clients or individual retailers, corporations, governments, etc. These wide variety of participants take part in the competition of relatively scarce resources – a handful of major currencies. In contrast, stock market usually contains thousands of stocks across different industries. Therefore, according to the adaptive market hypothesis of Lo (2004), foreign exchange market is likely to be more efficient comparing with stock market in terms of incorporating relevant information into its prices.[19] Therefore, the technical indicators from foreign exchange market may reveal additional information useful for predicting equity risk premium that has not been timely reflected by stock market.

Finally, Baker and Wurgler (2007) show that the sentiment changes index is positively corre-

---

[19]However, both foreign exchange market and stock market can still be inefficient and they can still be predictable as documented in the literature.

lated with equity risk premium. Therefore, a predictor, such as FX, SM or ECON, may obtain some of its predictive ability through predicting the changes of sentiment ($\Delta SENT$). As shown in Panel C of Table 4, we use FX, SM or ECON to predict $\Delta SENT$, under the in-sample one-regime regression model,

$$\Delta SENT_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{23}$$

and the data of $\Delta SENT$ is from Baker and Wurgler (2007). The results show that FX has the highest R^2 among three predictors and it is 9.2 times of the R^2 of ECON.[20] This indicates a strong predicting ability of FX in forecasting $\Delta SENT$ while a much weaker predicting ability of ECON.

To further examine whether FX is predicting the equity risk premium through forecasting $\Delta SENT$ while ECON is not, we conduct the following analysis based on forecasting residuals. Let,

$$r_{t+1} = \alpha + \beta \Delta SENT_{t+1} + \varepsilon^*_{t+1} \tag{24}$$

and

$$\varepsilon^*_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{25}$$

where ε^*_{t+1} is the residual component after removing the $\Delta SENT$ component from equity risk premium. We then use FX, SM or ECON to predict this residual component of equity risk premium. The results (not reported in Table 4) show that after excluding $\Delta SENT$, ECON becomes the best predictor which has an R^2 of 1.96% while FX only has an R^2 of 1.03% that is 47% less than ECON. Nevertheless, in Table 3, the R^2 of FX is just 7% less than ECON. This indicates that after taking out the $\Delta SENT$ component, the predicting power of FX is reduced a lot compared with ECON. Therefore, FX seems indeed deriving much of its predictive ability from predicting $\Delta SENT$. Hence, although both ECON and FX appear to be able to forecast equity risk premium as shown in Table 4, FX turns out to capture some different information useful for forecasting equity risk premium compared with the information captured by ECON (one is related to $\Delta SENT$ while the other is not). Overall, by incorporating FX on top of SM and ECON, we may capture additional information, capture information at a more timely manner and therefore achieve better predicting performance than without utilizing FX. In the next section, we will illustrate that the incorporation of the information of FX on top of SM and ECON can produce significant certainty equivalent return gain from an investment perspective.

---

[20]In the two-regime predictive regression model, the two regimes are determined by $\Delta SENT$. Knowing the regime already provides information on the value of $\Delta SENT$ for the next period. Therefore, we do not report in Table 4 the results corresponding the two-regime predictive regression model. Nevertheless, the R^2 of FX predicting $\Delta SENT$ based on two-regime predictive regression model is still the highest among these three predictors, and it is 42% larger than ECON.

3.5 Asset allocation

In this section, we examine the importance of incorporating technical indicators from foreign exchange market on top of technical indicators from stock market and macroeconomic variables from an investment perspective. Certainty equivalent return gain can be deemed as the portfolio management fee, which in form of annualized percentage return, that an investor would be willing to pay to obtain the access to the out-of-sample predictive regression forecasts based on the predictors given in the first column of Table 5 relative to the historical average benchmark forecast. We calculate the certainty equivalent return gain of equity risk premium predictors for a mean-variance investor with risk aversion coefficient of five by following Campbell and Thompson (2008). This investor dispenses monthly across stock and risk-free bill using one of the seven approaches listed in the first column of Table 5 to forecast returns or using the historical mean as the forecasting returns.

As shown by the second column of Table 5, which is for the overall period denoted as *all* in Table 5, the incorporation of FX on top of SM and ECON increases the certainty equivalent return gain from 5.60% for SM+ECON to 6.79% for FX+SM+ECON. Moreover, FX has the largest certainty equivalent return gain of 5.32% among the three channels when only one channel is used alone. In addition, in the third and fourth column, when we separate the sample into up-regime and down-regime, again, the incorporation of FX on top of SM and ECON increases the certainty equivalent return gain for the up-regime from 4.80% for SM+ECON to 8.00% for FX+SM+ECON.[21]

For the last column, we consider the certainty equivalent return gain which are calculated by assuming a proportional transactions cost equal to 50 basis points per transaction (e.g., Balduzzi and Lynch 1999). Now, the certainty equivalent return gain increases for more than 100% from 1.07% to 2.44% when incorporating FX on top of SM and ECON. Moreover, FX still has the largest certainty equivalent return gain of 3.08% among the three channels when only one channel is used alone, while ECON has the lowest gain. Furthermore, among the combined predictors, FX+SM displays the highest gain of 4.22%, followed by FX+SM+ECON with the second largest gain of 2.44%.

Overall, from an investment perspective, this table shows that the incorporation of technical indicators from foreign exchange market on top of technical indicators from stock market and macroeconomic variables can produce significantly higher certainty equivalent return gain than without the incorporation of FX information.

---

[21]When incorporating FX on top of SM and ECON, there is a small reduction in the certainty equivalent return gain for the down-regime.

4 Conclusion

This paper is the first to utilize technical indicators from foreign exchange market to forecast the equity risk premium and compare their performance with that of macroeconomic variables and technical indicators from stock market. The reasons to extend the frontier of technical indicators used in predicting equity risk premium from stock market to foreign exchange market are as follows. Firstly, foreign exchange market reflects various economic fundamentals potentially useful for predicting equity risk premium, though may not be fully reflected by available macroeconomic variables. Moreover, the technical indicators from foreign exchange market may provide useful information on predicting equity risk premium through the connections between foreign exchange market and stock market. Furthermore, given that the changes of sentiment are correlated with stock returns, foreign exchange market may provide forecasting power through predicting investors' changes of sentiment.

We find that technical indicators from foreign exchange market exhibit statistically and economically significant in-sample and out-of-sample forecasting power for the monthly equity risk premium, clearly on par with the documented forecasting power of macroeconomic variables and technical indicators from stock market from the literature. Moreover, we find that technical indicators from foreign exchange market capture additional information relevant for forecasting the equity risk premium beyond macroeconomic variables and technical indicators from stock market. In line with this finding, we show that combining information from technical indicators from foreign exchange market on top of technical indicators from stock market and macroeconomic variables produces superior equity risk premium forecasts and offers significant certainty equivalent return gain to investors by better tracking the cross time fluctuations in the equity risk premium.

Reference

Ang, A., G. Bekaert. 2007. Return predictability: Is it there? *Review of Financial Studies* 20, 651-707.

Ang, A., J. Chen. 2002. Asymmetric correlations of equity portfolios. *Journal of Financial Economics* 63, 443-494.

Baker, M., J. Wurgler. 2006. Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance* 61, 1645-1680.

Baker, M., J. Wurgler. 2007. Investor sentiment in the stock market. *National Bureau of Economic Research Cambridge, Mass., USA*.

Balduzzi, P., A. W. Lynch. 1999. Transaction costs and predictability: Some utility cost calculations. *Journal of Financial Economics* 52, 47-78.

Bergman, N. K., S. Roychowdhury. 2008. Investor Sentiment and Corporate Disclosure. *Journal of Accounting Research* 46, 1057-1083.

Billingsley, R. S., D. M. Chance. 1996. Benefits and limitations of diversification among commodity trading advisors. *The Journal of Portfolio Management* 23, 65-80.

Blume, L., D. Easley, M. O'hara. 1994. Market statistics and technical analysis: The role of volume. *The Journal of Finance* 49, 153-181.

Brown, D.P., R.H.Jennings. 1989. On technical analysis. *Review of Financial Studies* 2, 527-551.

Campbell, J. Y., R. J. Shiller. 1988a. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1, 195-228.

Campbell, J. Y., R. J. Shiller. 1988b. Stock prices, earnings, and expected dividends. *Journal of Finance* 43, 661-676.

Campbell, J. Y., T. Vuolteenaho. 2004. Inflation illusion and stock prices. *American Economic Review* 94, 19-23.

Chen, Y., K. Rogoff, B. Rossi. 2010. Can exchange rates forecast commodity prices. *Quarterly Journal of Economics* 125, 1145-1194.

Choi, J. J., T. Hiraki, N. Takezawa. 1998. Is foreign exchange risk priced in the Japanese stock market? *Journal of Financial and Quantitative Analysis* 33, 361-382.

Clark, T. E., M. W. McCracken. 2009. Improving forecast accuracy by combining recursive and rolling forecasts. *International Economic Review* 50, 363-395.

Clark, T. E., M. W. McCracken. 2012. Reality checks and nested forecast model comparisons. *Journal of Business and Economic Statistics*, forthcoming.

Clark, T. E., K. D. West. 2007. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* 138, 291-311.

Clements, M. 2010. Technical Analysis in Foreign Exchange Markets *Global Markets Media Ltd, Guilford, UK*.

Cochrane, J. H. 2001. Asset Pricing. *Princeton, NJ: Princeton University Press*.

Cochrane, J. H. 2008. The dog that did not bark: A defense of return predictability. *Review of Financial Studies* 21, 1533-1575.

Cooper, M., H. Gulen. 2004. Is time-series based predictability evident in real-time? *Working paper*.

Cooper, M.J., Gutierrez Jr., R.C., Hameed, A. 2004. Market States and Momentum. *Journal of Finance* 59, 1345-1365.

Covel, M. W. 2005. Trend Following: How Great Traders Make Millions in Up or Down Markets. *Prentice-Hall, New York*.

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

Fama, E. F., K. R. French. 1988. Dividend yields and expected stock returns. *Journal of Financial Economics* 22, 3-25.

Fama, E. F., G. W. Schwert. 1977. Asset returns and inflation. *Journal of Financial Economics* 5, 115-146.

Ferguson, R., JL. Treynor. 1985. In defense of technical analysis. *Journal of Finance* 40, 757-773.

Frankel, J. A., K. A. Froot. 1990. Chartists, Fundamentalists, and Trading in the Foreign Exchange Market. *American Economic Review* 80, 181-185.

Goh, J., F. Jiang, J. Tu, G. Zhou. 2012. Forecasting Government Bond Risk Premia Using Technical Indicators. *Working paper, SMU*.

Goyal, A., I. Welch. 2003. Predicting the equity premium with dividend ratios. *Management Science* 49, 639-654.

Goyal, A., I. Welch. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21, 1455-1508.

Guo, H. 2006. On the out-of-sample predictability of stock market returns. *Journal of Business* 79, 645-670.

Grundy, B.D., M. McNichols. 1989. Trade and the revelation of information through prices and direct disclosure. *Review of financial Studies* 2, 495-526.

Hau, H., H. Rey. 2006. Exchange rates, equity prices, and capital flows. *Review of Financial Studies* 19, 273-317.

Henkel, S. J., J. S. Martin, F. Nadari. 2011. Time-varying short-horizon predictability. *Journal of Financial Economics* 99, 560-580.

Hjalmarsson, E. 2010. Predicting global stock returns. *Journal of Financial and Quantitative Analysis* 45, 49-80.

Huang, D., G. Zhou. 2012. Economic and market conditions: two state variables that predict the stock market. *Working paper. Washington University at St. Louis.*

Jiang F., J. Tu, G. Zhou. 2013. Investor Sentiment Aligned: A Powerful Predictor of Stock Returns. *Working paper*.

Jorion, P. 1991. The pricing of exchange rate risk in the stock market. *Journal of Financial and Quantitative Analysis* 26, 363-376.

Keim, D. B., R. F. Stambaugh. 1986. Predicting returns in the stock and bond markets. *Journal of Financial Economics* 17, 357-390.

Kho, B. 1996. Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets. *Journal of Financial Economics* 41, 249-290.

LeBaron, B. 1999. Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics* 49, 125-143.

Lemmon M., E. Portniaguina. 2006. Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies* 19, 1499-1529.

Lettau, M., V. Van Nieuwerburgh. 2008. Reconciling the return predictability evidence. *Review of Financial Studies* 21, 1607-1652.

Li, J., J. Yu. 2012. Investor Attention, Psychological Anchors, and Stock Return Predictability. *Journal of Financial Economics* 104, 401-419. Lo, A. W. 2004. The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management*.

Lo, A. W., J. Hasanhodzic. 2010. The Evolution of Technical Analysis: Financial Prediction from Babylonian Tablets to Bloomberg Terminals. *John Wiley & Sons, Hoboken, New Jersey*.

Lo, A. W., H. Mamaysky, J. Wang. 2000. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance* 55, 1705-1765.

Ludvigson, S. 2004. Consumer confidence and consumer spending. *Journal of Economic Perspectives* 18, 29-50.

Menkhoff, L., M. P. Taylor. 2007. The obstinate passion of foreign exchange professionals: Technical analysis. *Journal of Economic Literature* 45, 936–972.

Neely, C. J. 2002. The temporal pattern of trading rule returns and exchange rate intervention: Intervention does not generate technical trading profits. *Journal of International Economics* 58, 211-232.

Neely, C. J., P. A. Weller, R. Dittmar. 1997. Is technical analysis in the foreign exchange market

profitable? A genetic programming approach. *Journal of Financial and Quantitative Analysis* 32, 405-426.

Neely, C. J., D. E. Rapach, J. Tu, G. Zhou. 2012. Forecasting the equity risk premium: The role of technical indicators. Federal Reserve Bank of St. *Louis working paper 2010-008C*.

Nelson, C. R. 1976. Inflation and the rates of return on common stock. *Journal of Finance* 31, 471-483.

Osler, C. L. 2003. Currency orders and exchange rate dynamics: An explanation for the predictive success of technical analysis, *The Journal of Finance* 58, 1791-1820.

Park, C. H., S. H. Irwin. 2007. What do we know about the profitability of technical analysis? *Journal of Economic Surveys* 21, 786-826.

Pettenuzzo, D., A. Timmermann. 2011. Predictability of stock returns and asset allocation under structural breaks. *Journal of Econometrics* 164, 60-78.

Rapach, D. E., J. K. Strauss, G. Zhou. 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies* 23, 821-862.

Rozeff, M. S. 1984. Dividend yields are equity risk premiums. *Journal of Portfolio Management* 11, 68-75.

Schwert, G. W. 1989. Why does stock market volatility change over time? *Journal of Finance* 44, 1115-1153.

Schwert, G. W. 1990. Stock volatility and the crash of 87. *Review of Financial Studies* 3, 77-102.

Shen, J., J. Yu. 2012. Investor sentiment and economic forces. *Working paper*.

Zhu, Y., G. Zhou. 2009. Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics* 92, 519-544.

Table 1: Summary Statistics, 1973:01-2010:12

Variable	Mean	Standard deviation	Minimum	Maximum	Sharpe ratio
log equity risk premium	0.32	4.59	-24.84	14.87	0.07
DP	-3.59	0.46	-4.52	-2.75	
DY	-3.58	0.46	-4.53	-2.75	
EP	-2.82	0.52	-4.84	-1.90	
DE	-0.77	0.35	-1.22	1.38	
SVAR	0.25	0.49	0.02	6.55	
BM	0.51	0.30	0.12	1.21	
NTIS	0.01	0.02	-0.06	0.05	
TBL	5.58	3.19	0.03	16.30	
LTY	7.60	2.49	3.03	14.82	
LTR	0.73	3.15	-11.24	15.23	
TMS	2.02	1.55	-3.65	4.55	
DFY	1.12	0.48	0.55	3.38	
DFR	0.00	1.42	-9.75	7.37	
INFL	0.36	0.38	-1.92	1.79	

Notes. The table reports summary statistics for the log equity risk premium and 14 macroeconomic variables. The data are from Amit Goyal's web page at http://www.hec.unil.ch/agoyal/. The macroeconomic variables are defined as follows: DP = log dividend-price ratio, DY = log dividend yield, EP = log earnings-price ratio, DE = log dividend-payout ratio, SVAR = stock variance, BM = book-to-market ratio, NTIS = net equity expansion, TBL = treasury bill rate (annual %), LTY = long-term bond yield (annual %), LTR = long-term bond return(%), TMS = term spread (annual %), DFY = default yield spread (annual %), DFR = default return spread (%), INFL = inflation rate(%). The Sharpe ratio is the mean of the log equity risk premium divided by its standard deviation.

Table 2: Predictive Regression Results Based on Macroeconomic Variables

Predictor	β^{up}	β^{down}	R^2-up	R^2-down	R^2	R^2_{os}-up	R^2_{os}-down	R^2_{os}
DP	-0.53 [-0.85]	1.39 [2.01]	0.32	1.73	2.15	3.61**	0.63**	2.02***
DY	-0.46 [-0.73]	1.38 [1.99]	0.24	1.70	2.10	2.99**	0.86**	1.86***
EP	-0.97 [-1.79]	1.44 [2.29]	1.41	2.26	2.91	2.64**	-2.17	0.08**
DE	1.16 [1.50]	-0.71 [-0.72]	1.00	0.23	1.59	-1.99	-8.40	-5.40
SVAR	-1.05 [-1.82]	-1.17 [-1.79]	1.46	1.38	2.44	-8.62	0.68	-3.67
BM	-1.12 [-1.20]	1.30 [1.21]	0.64	0.64	1.68	3.27**	1.63**	2.40***
NTIS	6.91 [0.49]	-12.09[-0.75]	0.11	0.24	1.22	1.23	-2.75	-0.88
TBL	-0.15 [-1.68]	0.05 [0.50]	1.25	0.11	1.63	-0.04	0.26	0.12*
LTY	-0.12 [-0.99]	0.10 [0.83]	0.43	0.30	1.39	2.57**	0.88	1.67**
LTR	0.10 [1.10]	0.17 [1.64]	0.54	1.17	1.93	-1.03	-0.73	-0.87
TMS	0.34 [1.87]	0.08 [0.36]	1.55	0.06	1.73	-3.70	1.78**	-0.78
DFY	0.71 [1.28]	-0.15 [-0.21]	0.73	0.02	1.36	-7.36	-0.33	-3.62
DFR	0.71 [3.76]	-0.10 [-0.41]	5.96	0.07	3.62	11.03**	-0.68	4.80**
INFL	-0.84 [-1.06]	1.30 [1.62]	0.05	1.13	1.89	-2.02	0.71	-0.57

Notes. The table reports estimation results for the two-regime predictive regression model,

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta^{up}x_t + \varepsilon^{up}_{t+1} \\ \alpha^{down} + \beta^{down}x_t + \varepsilon^{down}_{t+1} \end{cases} \tag{26}$$

where r_{t+1} is the log equity risk premium and x_t is one of the 14 macroeconomic variables given in the first column. β^{up} and β^{down} are the slope coefficients in up- and down- regimes. The value in brackets report heteroskedasticity-consistent t-statistics. R^2 (in percent) is the in-sample R-squared and R^2_{os} (in percent) is the Campbell and Thompson (2008) out-of-sample R-squared over 1993:01-2010:12. Statistical significance for R^2_{os} is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R^2_{os} \leq 0$ against $H_A : R^2_{os} > 0$. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. For R^2-up and R^2-down are the R^2 of two regimes determined by the sentiment changes index of Baker and Wurgler (2007). And also the same case for R^2_{os}-up and R^2_{os}-down which are the R^2_{os} of two regimes.

Table 3: Predictive Regression Results Based on Combined Information

Predictor	β^{up}	β^{down}	R^2-up	R^2-down	R^2	R^2_{os}-up	R^2_{os}-down	R^2_{os}
ECON	-0.17 [-1.39]	0.22 [1.59]	0.86	1.10	1.96	2.73**	1.4**	2.02***
FX	0.10 [1.62]	0.08 [1.20]	1.16	0.62	1.82	4.60***	2.57*	3.52***
SM	0.04 [0.92]	0.09 [1.65]	0.37	1.19	1.81	3.35***	0.42	1.79**
FX+ECON	0.09 [1.54]	0.09 [1.37]	1.03	1.04	2.44	5.33***	1.96*	3.54***
	-0.16 [-1.31]	0.24 [1.72]						
SM+ECON	0.04 [0.87]	0.10 [1.88]	0.31	1.76	2.54	4.01***	0.28	2.02***
	-0.17 [-1.36]	0.25 [1.83]						
FX+SM	0.06 [1.24]	0.10 [1.85]	0.55	0.63	2.00	5.80***	1.09	3.29***
	0.08 [1.30]	0.02 [0.23]						
FX+SM+ECON	0.05 [1.18]	0.11 [2.11]	0.84	1.75	2.98	6.28***	0.86*	3.40***
	0.08 [1.25]	0.02 [0.27]						
	-0.16 [-1.29]	0.26 [1.89]						

Notes. The table reports estimation results for a predictive regression model based on principal components. The ECON is the first principal component of 14 macroeconomic variables. The SM is the first principal component of 56 technical indicators from stock market. The FX is the first principal component of 35 technical indicators from foreign exchange market. The FX+ECON is based on the regression model

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} FX_t + \beta_2^{up} ECON_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} FX_t + \beta_2^{down} ECON_t + \varepsilon_{t+1}^{down} \end{cases} \qquad (27)$$

The SM+ECON is similar to FX+ECON. And for the FX+SM is based on the first two principal components which generated from all 91 technical indicators. The FX+SM+ECON is based on the regression model that combining FX+SM with ECON.

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} PC_t^1 + \beta_2^{up} PC_t^2 + \beta_3^{up} ECON_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} PC_t^1 + \beta_2^{down} PC_t^2 + \beta_3^{down} ECON_t + \varepsilon_{t+1}^{down} \end{cases} \qquad (28)$$

β^{up} and β^{down} are the slope coefficients in up- and down- regimes. The value in brackets report heteroskedasticity-consistent t-statistics. R^2 (in percent) is the in-sample R-squared and R^2_{os} (in percent) is the Campbell and Thompson (2008) out-of-sample R-squared over 1993:01-2010:12. Statistical significance of R^2_{os} is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R^2_{os} \leq 0$ against $H_A : R^2_{os} > 0$; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. For R^2-up and R^2-down are the R^2 of two regimes determined by the sentiment changes index of Baker and Wurgler (2007). And also the same case for R^2_{os}-up and R^2_{os}-down which are the R^2_{os} of two regimes.

Table 4: Reasons for the Additional Predictability of Foreign Exchange Market

	R^2	β	t-stat
Panel A: FX predicts equity risk premium of stock market			
one-regime	1.03	0.10	2.17
two-regime	1.82	0.10	1.62
		0.08	1.20
Panel B: SM predicts foreign exchange market returns			
one-regime	0.07	0.01	0.55
two-regime	0.64	0.03	1.04
		-0.01	-0.05
Panel C: Predicting changes of sentiment			
ECON	0.14	0.02	0.78
FX	1.29	0.02	2.43
SM	0.34	0.01	1.25

Notes. The table reports the in-sample results of three different types of regression models. The Panels A and B describe the predictability disparity between the foreign exchange market and stock market. We use the first principal component of technical indicators from foreign exchange market (FX) to predict the equity risk premium of stock market (Panel A) and the first principal component of technical indicators from stock market (SM) to predict the foreign exchange market returns (Panel B). For the one-regime case, we use the conventional standard regression model.

$$r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{29}$$

And for the two-regime case, the predictive regression model is defined as follows,

$$r_{t+1} = \begin{cases} \alpha^{up} + \beta_1^{up} X_t + \varepsilon_{t+1}^{up} \\ \alpha^{down} + \beta_1^{down} X_t + \varepsilon_{t+1}^{down} \end{cases} \tag{30}$$

Panel C illustrates the predictive ability of the first principal component of macroeconomic variables (ECON), FX and SM in forecasting the changes of sentiment ($\Delta SENT$) provided by Baker and Wurgler(2007).
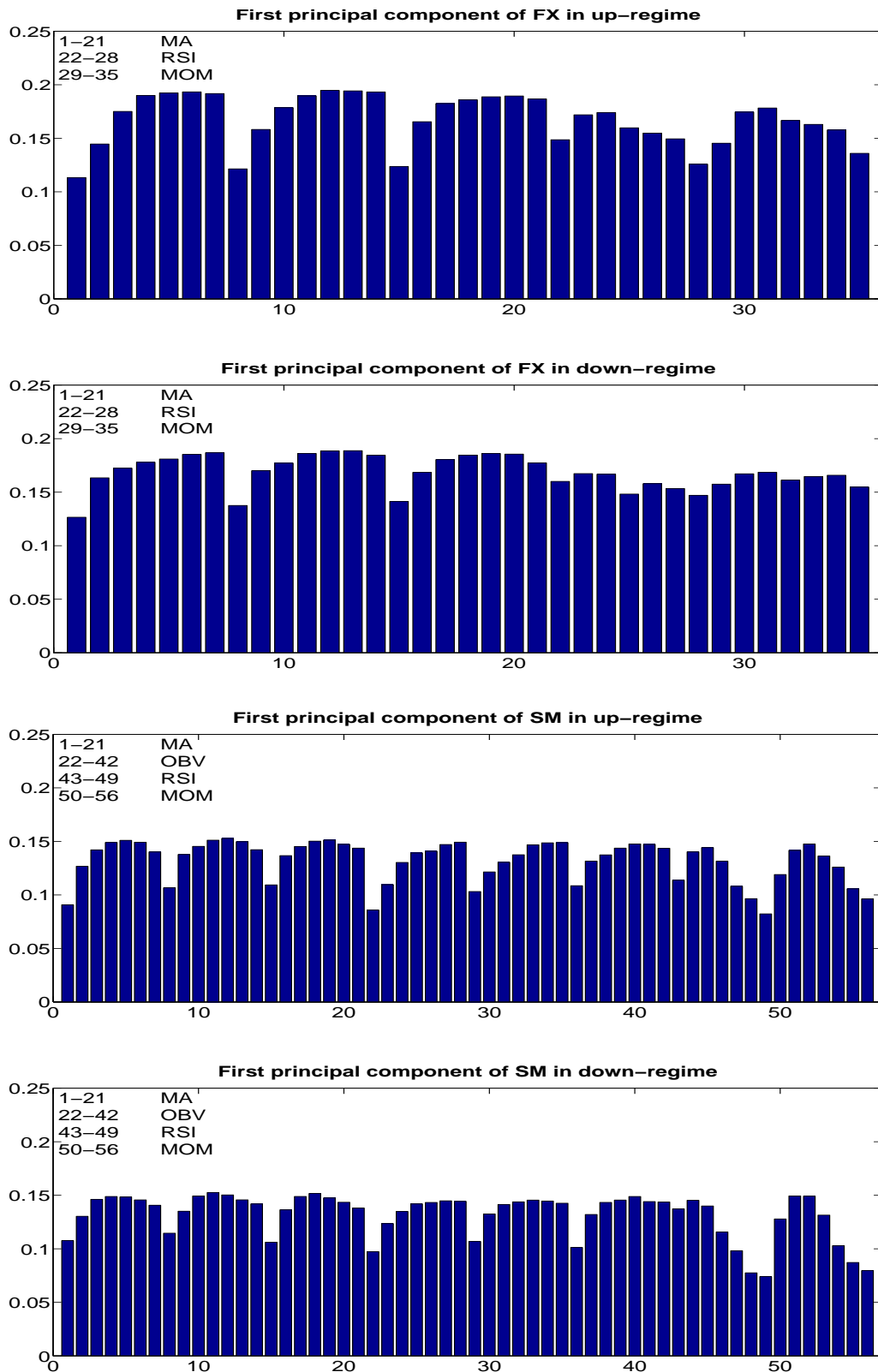
$$\Delta SENT_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{31}$$

Table 5: Certainty Equivalent Return Gain

Predictor	Δ_{all}	Δ_{up}	Δ_{down}	Δ_{50bps}
ECON	4.21	2.06	6.85	-0.53
FX	5.32	6.63	4.24	3.08
SM	3.44	3.84	3.32	0.72
FX+ECON	5.45	5.03	6.44	0.92
SM+ECON	5.60	4.80	6.84	1.07
FX+SM	6.75	10.68	3.15	4.22
FX+SM+ECON	6.79	8.00	6.12	2.44

Notes. The table reports the annualized certainty equivalent return gain (in percent) for a mean-variance investor with relative risk aversion coefficient of five who dispenses monthly across stock and risk-free bill using one of the seven approaches (the first column) to forecast returns or using the historical average as the forecasting returns. Certainty equivalent return gain is computed for the entire forecast evaluation period 1993:01-2010:12 (the second column) and separately for up-regime (the third column) and down-regime (the fourth column). And for the last column, it is the annualized certainty equivalent return gain assuming a proportional transactions cost of 50 basis points per transaction.

Figure 1: Factor Loadings, Principal Components Extracted from FX or SM, 1973:01-2010:12

First principal component of FX in up−regime

1−21	MA
22−28	RSI
29−35	MOM

First principal component of FX in down−regime

1−21	MA
22−28	RSI
29−35	MOM

First principal component of SM in up−regime

1−21	MA
22−42	OBV
43−49	RSI
50−56	MOM

First principal component of SM in down−regime

1−21	MA
22−42	OBV
43−49	RSI
50−56	MOM

Notes. The figure shows the weights of the first principal component of 35 technical indicators from foreign exchange market and the weights of the first principal component of 56 technical indicators from stock market. The text-box in each figure shows the order of those technical indicators. These four pictures indicate a consistent patent for both up- and down- regimes which exhibit FX and SM acts like a consensus indicator that averages out the information across different technical rules.

Figure 2: Factor Loadings, Principal Components Extracted from FX and SM, 1973:01-2010:12

First principal component of FX+SM in up−regime

1−21	FX−MA
22−28	FX−RSI
29−35	FX−MOM
36−56	SM−MA
57−77	SM−OBV
78−84	SM−RSI
85−91	SM−MOM

First principal component of FX+SM in down−regime

1−21	FX−MA
22−28	FX−RSI
29−35	FX−MOM
36−56	SM−MA
57−77	SM−OBV
78−84	SM−RSI
85−91	SM−MOM

Second principal component of FX+SM in up−regime

1−21	FX−MA
22−28	FX−RSI
29−35	FX−MOM
36−56	SM−MA
57−77	SM−OBV
78−84	SM−RSI
85−91	SM−MOM

Second principal component of FX+SM in down−regime

1−21	FX−MA
22−28	FX−RSI
29−35	FX−MOM
36−56	SM−MA
57−77	SM−OBV
78−84	SM−RSI
85−91	SM−MOM

Notes. The figure shows the weights of the first two principal components of 91 technical indicators from foreign exchange market and stock market. The text-box in each figure shows the order of those technical indicators. These four pictures demonstrate the dominant ability of technical indicators from foreign exchange market (FX) in the second principal component and the dominant ability of technical indicators from stock market (SM) for the first principal component which indicate the equal importance of the first two principal components and the difference of the information captured by FX and SM.

32